

Assessing transportation networks vulnerability for the decision making in humanitarian logistics

By

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To my children Matthew, Camilo and Lauren
My inspiration, and the reason I undertook this great dream

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CONTENTS

ABSTRACT	11
1 INTRODUCTION AND CONTRIBUTIONS	13
1.1. Introduction	13
1.2. Contributions	19
1.2.1. Advanced Econometric Methods and Models for DCFs Estimation.	19
1.2.2. A vulnerability Assessment Model of Transportation Networks for the Decision Making in Humanitarian Logistics.	20
2 LITERATURE REVIEW AND THEORETICAL BACKGROUND	21
2.1. Objective Functions in Humanitarian Logistics	21
2.2. Economic Valuation Techniques	25
2.3. Description of the Methodology to Estimate DCFs	28
2.3.1. Notation	28
2.3.2. Economic Foundation	29
2.3.3. DCFs and Latent Variables in Disaster Contexts.	36
2.3.4. Modelling with Latent Variables	36
2.4. Vulnerability in Transportation Networks	40
2.4.1. Vulnerability	41
2.4.2. Accessible and Resilient Transportation Networks	44
3 ASSESSING ECONOMIC IMPACTS OF HUMANITARIAN RELIEF DISTRIBUTION	48
3.1. Introduction	48
3.2. Experimental Setup I: Providing Drinking Water as a Scarce Supply	49
3.3. Models Specifications	55
3.3.1. Functional Forms	56
3.4. Results and Analysis	58
3.5. Conclusions	63

4	INFLUENCE OF INDIVIDUAL'S SOCIOECONOMIC CHARACTERISTICS AND RANDOM EFFECTS ON DEPRIVATION COST FUNCTIONS	65
4.1.	Introduction	65
4.2.	Experimental Setup II: Providing a Basic Food Kit as a Scarce Supply	67
4.3.	Models Specifications with Systematic and Random Variation	74
4.4.	Results and Analysis	79
4.5.	Conclusions	84
5	INFLUENCE OF ATTITUDES AND PERCEPTIONS ON DEPRIVATION COST FUNCTIONS	86
5.1.	Introduction	86
5.2.	Data for Latent Variables	87
5.3.	Models Specifications with Latent Variables	89
5.3.1.	Structural Equations	92
5.3.2.	Measurement Equations	94
5.4.	Results and Analysis	94
5.5.	Conclusions	100
6	ASSESSING VULNERABILITY OF TRANSPORTATION NETWORKS FOR HUMANITARIAN RELIEF OPERATIONS	102
6.1.	Introduction	102
6.2.	The proposed Vulnerability Model	103
6.3.	Numerical Experiments	108
6.3.1.	Experimental Setup I: A Small Network With a Single Origin-Destination Pair	110
6.3.2.	Experimental Setup II: A Large Network With Several Origin-Destination Pairs	113
6.4.	Empirical Analyses: The Colombian Coffee Zone Road Network	119
6.4.1.	Specifications and Data	119
6.4.2.	Results	120
6.5.	Conclusions	123

7	OVERALL CONCLUSIONS AND CHALLENGES FOR THE FUTURE _____	124
7.1.	Overall Conclusions_____	124
7.2.	Future Researches_____	127
8	REFERENCES AND APPENDICES _____	128
8.1.	References _____	128
8.2.	Appendices _____	145

LIST OF TABLES

Table 1. <i>Vulnerability analysis models of transportation networks</i>	43
Table 2: <i>Variables in Experimental Design</i>	52
Table 3: <i>Summary Statistics</i>	54
Table 4: <i>Econometric Models</i>	59
Table 5: <i>Direct Elasticities in the Choice Model</i>	61
Table 6. <i>Attributes of experimental design</i>	70
Table 7. <i>Socioeconomic characteristics of the sample</i>	73
Table 8. <i>Attributes used in the specification of utility functions.</i>	76
Table 9. <i>Models Specifications</i>	78
Table 10. <i>Modeling results</i>	81
Table 11. <i>Latent variable indicators and levels</i>	88
Table 12. <i>Estimated HLVD CMs</i>	95
Table 13. <i>Results of the experimental setup I</i>	112
Table 14. <i>Vulnerability indicators for disruption scenarios in the experimental setup I</i>	113
Table 15. <i>Optimal distribution strategy assumed for the experimental setup II</i>	114
Table 16. <i>Critical scenarios with two links in the southwestern Colombia road network</i>	122

LIST OF FIGURES

Figure 1. Deprivation Cost Functions	23
Figure 2. Relationship of deprivation costs/benefits	35
Figure 3. HLVDcMs structure	40
Figure 4. Recovery of a system	46
Figure 5. Impact and recovery in the transportation system	47
Figure 6: Study Area in the Colombian Caribbean region	50
Figure 7: Costs for Water Deprivation	61
Figure 8: Deprivation Cost Elasticities	62
Figure 9. Study Area in Colombian	68
Figure 10. DCF for the first family of ML models	83
Figure 11. DCF for the second family of ML models.	83
Figure 12. Deprivation time elasticity of DCFs	84
Figure 13. Rate of the LVs indicators	89
Figure 14. Integrated choice and latent variable model	91
Figure 15. Deprivation cost functions	98
Figure 16. DCF used for network vulnerability model	110
Figure 17. Network Topology in the experimental setup I	111
Figure 18. Structure of the Sioux Falls Network	114
Figure 19. Model results with disruption scenarios of a link in the experimental setup II	115
Figure 20. Simultaneous disruption of 2 links in the experimental setup II	116
Figure 21. Effect of synergy in critical combinations of 2 links in the experimental setup II	117
Figure 22. Links Frequency by range vulnerability and disruption scenarios	118
Figure 23. Simultaneous disruption of 2 links without air link connections	119
Figure 24. The southwestern Colombia road network	120
Figure 25. Critical links on the southwestern Colombia road network	121

LIST OF APENDICES

<i>Appendix 1. 2nd Survey applied.</i>	145
<i>Appendix 2. Example of the stated preference survey cards used</i>	146
<i>Appendix 3. Questionnaire of perception indicators</i>	147
<i>Appendix 4. Estimated threshold for each indicator</i>	148
<i>Appendix 5. Pseudocode model for the transportation network vulnerability</i>	149

ABSTRACT

Transportation networks are vulnerable to natural disasters, which can degrade their functionality and generate negative impacts over people, especially during the emergency phase, where timely access of humanitarian operations is critical. An interruption of humanitarian relief supply chains in the aftermath of a disaster increases the human suffering (deprivation costs) resulting from the lack of access to essential goods or services. These costs are generally not considered in the mathematical formulations used for assessing vulnerability in transportation networks, which can lead to inappropriate strategies for humanitarian assistance. Consequently, this doctoral thesis presents a vulnerability assessment model for the development of high impact humanitarian logistics operations. The model is based on an economic analysis that involves both the logistical costs of humanitarian distribution operations and the deprivation costs derived from the delays in the provision of basic supplies. These latter have been estimated using advanced econometric models (Logit Multinomial, Mixed Logit and Hybrid Latent Variable - Discrete Choice Models) according to the theory of discrete choices. These models consider the influence of people's attitudes and perceptions as well as their socioeconomic characteristics. Their results are used to evaluate the monetary value of deprivation, which is included into the vulnerability analysis.

The vulnerability model presented is particularly useful for planning resilient humanitarian logistic chains in the pre-disaster stages and prioritizing the rehabilitation (access restoration) of the post-disaster broken links. The model is suitable for disaster preparedness and mitigation planning phases. The identification of critical links in transportation networks allows planners and decision makers to achieve a more robust aid distribution strategy. The model estimates the optimal social outcome based on the suffering brought about by the delays in the provision of basic supplies using social costs. In addition to

numerical experiments using case study networks, the author implemented the model to the coffee-producing region of Colombia, which was hit by an earthquake in 1999.

1 INTRODUCTION AND CONTRIBUTIONS

1.1. Introduction

Natural disasters affect thousands of people each year in many countries around the world. Most of them have the potential to cause catastrophic loss of life and physical destruction. Such disasters can have a major impact on people's quality of life and wellbeing. Moreover, their cumulative effects decrease opportunities for human development, especially in developing countries where their impacts are even greater. Most people in developing countries live in areas that are at high risk of natural disasters and extreme events or live in poorly constructed buildings, which become rubble or other vulnerable conditions that can cause massive human loss. Also, many urban areas in these countries do not have early warning programme or Emergency Response Systems (ERSs), making their populations especially vulnerable to natural disasters. According to the United Nations (2014), between 1994 and 2013, 4.4 billion people have been affected by disasters, claiming 1.3 million lives and generating more than US\$2 trillion in economic losses. These statistics illustrate the vulnerability of modern societies and the challenges for disaster responders.

When disasters or catastrophic events occur, in addition to impacting populations, the physical infrastructure and supporting systems, they also create uncertainty affecting the response itself. Demand for critical supplies such as water and food may increase due to the partial or total destruction of local inventories. Moreover, the flow of basic supplies is limited due to the collapse of distribution and transportation systems.

Affected populations have to cope and experience deprivation and suffering. The absence of functioning markets that prevents people from buying, selling or trading goods or services is one critical feature in this context (Holguín-Veras et al. 2013). As a result, the demand for critical supplies increases as well as the population's suffering, forcing to an almost immediate action from relief agencies in a race against time (Stauffer et al. 2016). The more the response is delayed, the lower the beneficiaries welfare and their ability to cope with the disaster impacts (Cohen 2008). Therefore, relief agencies must design a prioritized plan to provide life-saving emergency assistance for people in need in the short term. However, such prioritized plan must consider every group in the impacted population, especially the vulnerable as social inequities exacerbate suffering (OPS 2001). This represents a great challenge for relief responders who usually have to make such decisions on the basis of intuition and experience without the assistance of appropriate analytical tools.

Current methodologies typically use approaches based on commercial logistics, which are inappropriate for humanitarian logistics purposes (Holguín-Veras et al. 2012). In most disasters, the needs of impacted population are not met, so the most important consideration in relief operations is to maximize the effectiveness of the humanitarian aid and not necessarily to minimize the logistics costs. Consequently, trying to meet the affected people's needs using approaches based on commercial logistics does not lead to an optimal social outcome as the suffering brought about by the lack of access to a good or service is not internalized by survivors receiving the aid (Holguín-Veras et al. 2012). This measure of suffering is known as “deprivation costs” (DCs), which are externalities associated to the aid distribution after disasters (Holguín-Veras et al. 2013).

According to Holguín-Veras et al. (2016); Holguín-Veras et al. (2012b); Holguín-Veras et al. (2013); Pérez and Holguín-Veras (2015), all prioritized plans must be based on social costs minimization, thus allowing a socially optimal level of distribution of the scarce available resources. Such social costs are the summation of the impacts of those logistical decisions over all sectors of the society affected by the relief operation (Varian 1992). In general terms, social costs include the logistics costs carried out by the relief groups (e.g., inventory, transportation, delivering and distribution) and the direct impact on the population affected (deprivation costs) (Holguín-Veras et al. 2013). It is important to consider the impacts on the individuals who do not receive aid because their deprivation costs will increase as they wait for supplies. These additional costs are the opportunity costs of the delivery strategy, and are very important because, typically, the amount of distributed supplies do not meet all demands. Indeed, if the relief groups/agencies do not consider the deprivation costs in the decision-making process, the possibility of achieving effective outcomes diminishes as real needs created by the disaster are not satisfied and supplies take longer time to become available.

In such context, transportation networks play a major role in determining the deprivation costs experienced by the affected population because they facilitate the movement and access to goods and people in different areas. Therefore, network disruptions have significant impacts on society because they hinder evacuation procedures, emergency response, development of humanitarian supply chains, and the subsequent recovery of the affected areas. Delivery and response vehicles may have to travel longer distances (or may not be able to access at all), and there is considerable uncertainty about the state of the network (Holguín-Veras et al. 2012b). These factors can also increase travel times and costs for the relief agencies and lead to significant increases in

logistic costs (LCs) as well as the externalities associated with the event itself, e.g., deprivation costs, casualties, economic losses.

It is clear that disaster response times influence the welfare of those affected. The impacted population may be trapped, injured, at risk of death or emotionally and psychologically affected; and access to the affected areas by the disaster and humanitarian response operations is a critical issue that has not been considered in current network vulnerability formulations and analyses. The current approaches to assess vulnerability of transportation networks only consider some technical features related to transportation costs such as travel time (Chen et al. 2012; Jaller et al. 2015; Jenelius 2009; Jenelius and Mattsson 2012; Lu et al. 2014; Nagurney and Qiang 2009; Rodríguez-Núñez and García-Palomares 2014; Scott et al. 2006; Sullivan et al. 2010; Wang et al. 2016); generalized costs (Chen et al. 2007; Gómez et al. 2011; Jenelius et al. 2006; Luatkep et al. 2013; Qiang and Nagurney 2012; Taylor et al. 2006); network topological features (Qiang and Nagurney 2008; Sohn 2006; Taylor and D'Este 2005; Zhixin et al. 2010); and traffic flow and congestion effects (Balijepalli and Oppong 2014; Jenelius 2010; Rupi et al. 2015; Sohn 2006; Wang et al. 2016).

A comprehensive analysis of transportation network vulnerabilities for disaster response should include the impacts on social costs. Especially because social costs are an appropriate measure for cases where the decision process should consider the LCs and impacts (externalities) of the provision of services or supplies on a number of beneficiaries (Holguín-Veras et al. 2013).

To fully account for the socio-technical impacts of response and humanitarian operations, a comprehensive analysis of transportation network vulnerabilities should include social costs (Holguín-Veras et al. 2013). If such costs are not

listed in the analyses, humanitarian assistance strategies will not reach a socially optimum level. In addition, lack of consideration will also hamper the development of resilient humanitarian supply chains, especially in regions with high levels of risk. To fill this gap, this doctoral thesis proposes a valuation model of transportation network vulnerability that explicitly considers social costs and is particularly useful for the design and planning of humanitarian resilient supply chains, and to prioritize the rehabilitation (access restoration) of the post-disaster disrupted network.

This doctoral thesis is organized as follows: Chapter 2 provides an overview of the literature relevant and theoretical background. This chapter also include the economic foundation of a methodology proposed to quantify the economic impacts of relief distribution after disasters based on discrete choice models. In Chapter 3 a stated choice data about preferences for water purchases under different scenarios of deprivation is presented. The resulting DCs are estimated using the methodology proposed in chapter 2. The results presented show that the estimated models have microeconomic and statistical robustness and demonstrate that social benefits for timely delivery of critical supplies are considerably larger than the market price, highlighting that current humanitarian logistics models may underestimate the total costs of relief operations.

As different socio-economic groups in a disaster context experiment diverse needs and assistance, a proper and efficient humanitarian process should respond in a differentiated way considering the specific requirements of each group, especially the most vulnerable. In order to deal with this matter, Mixed Logit Models that consider systematic and random heterogeneity over individual preferences and responses are presented in Chapter 4, which allow adjusting Deprivation Costs Functions (DCFs) that are more equitable in order

to reach the social optimum. In this chapter, a stated choice survey was designed and applied to people living in areas affected by floods and earthquakes in Colombia. The resulting DCFs are useful for estimating the social costs of humanitarian relief operations.

Chapter 5 focuses on the estimation of DCFs, analyzing the role of psychosocial factors, such as people attitudes and perceptions and their relationship with the socioeconomic characteristics. These factors are fundamental to understand how individuals make decisions in order to achieve a better level of welfare in a disaster context. Base on data collected and presented in chapter 4, two Hybrid Discrete Choice Models (HDCMs) were estimated using maximum likelihood. Estimation process was based on 5040 observations from 560 respondents according to an efficient experimental design. The results demonstrate that risk perception, safety culture, and confidence on Emergency Response Systems, as Latent Variables, play a major role in the individual disaster preparedness and capturing people' heterogeneity for the estimation of DCFs.

In chapter 6 the transportation network vulnerability is analized based on social costs, which include the logistics cost associated with the relief distribution and the impacts of the relief effort on the beneficiaries. Being these impacts measured through the DCFs adjusted in the previous chapters (Chapters 3, 4 and 5). As a result, a vulnerability assessment model for transportation networks is presented, which allows identifying critical links for the development of high impact humanitarian logistics operations. In addition to numerical experiments using case study networks, the model was implemented in the coffee-producing region of Colombia, which was hit by an earthquake in 1999. The empirical results identify those links whose disruption increase

SCs highly, as opposed to only considering logistics costs. Finally, chapter 7 provides overall conclusions as well as directions for further research.

1.2. Contributions

The main contributions derived from this doctoral thesis are summarized as follows:

1.2.1. Advanced Econometric Methods and Models for DCFs

Estimation.

In chapters 3, 4 and 5 different econometric methods and models were developed for the economic valuation of deprivation costs derived from inequities humanitarian aid distribution in disaster contexts. These estimations provide a conceptually solid approach to assessing the complex tradeoffs frequently made under conditions of scarcity prevailing in the aftermath of large disasters. The estimations would allow relief organizations to determine the optimal way to allocate these scarce supplies, and minimize the social costs produced by the relief distribution. The chief implication is that there is no need to use proxy measures that cannot account for the effects of deprivation. It is clear that the mathematical models based on social costs may be more complex than those that use simpler objective functions. However, the additional effort is worthwhile as it leads to models that are more realistic and, as consequence, produce better allocation of resources. In overall terms, the economic valuation of this negative externality can be incorporated into comprehensive humanitarian logistics models to reach the social optimum through an effective resources allocation. The resulting DCFs are also useful to perform risk analysis as well as to conduct economic evaluation of humanitarian aid operations.

1.2.2. A vulnerability Assessment Model of Transportation Networks for the Decision Making in Humanitarian Logistics.

We propose a valuation model of transportation network vulnerability for humanitarian logistics purpose. The model explicitly considers social costs and is particularly useful for the design and planning of humanitarian resilient supply chains as well as to prioritize the rehabilitation of the post-disaster disrupted network. The model is suitable for disaster preparedness and mitigation planning phases. The identification of critical links in transportation networks allows planners and decision makers to achieve a more robust aid distribution strategy. Vulnerability analyses of transportation networks yield relevant information for the design of the distribution strategy. Specifically, the model estimates the optimal social outcome based on the suffering brought about by the delays in the provision of basic supplies using social costs.

2 LITERATURE REVIEW AND THEORETICAL BACKGROUND

This section provides an overview of the literature relevant to the objective functions that have been used in modeling humanitarian logistics, the valuation techniques available to estimate economic impacts of aid distribution, the economic foundation used to estimate DCFs and the vulnerability of transportation network.

2.1. Objective Functions in Humanitarian Logistics

The first formulations proposed to post-disaster humanitarian operations were inspired by commercial logistics. As such, the most commonly used objective function was the minimization of logistics cost, with no understanding of the impacts of the operations on the beneficiaries receiving the humanitarian aid (Holguín-Veras et al. 2012). Ignoring such impacts brings negative implications. In most post-disaster environments, the relief supplies available are frequently not sufficient to meet the needs of all those affected. As a result, relief agencies must decide on how best to allocate the scarce resources while, at the same time, account for their own logistic costs. Thus, the tradeoffs between impacts on beneficiaries and logistic costs ought to be considered.

Recognizing the limitations of initial approaches, researchers have attempted to define and formulate novel objective functions for use in humanitarian logistics (HL) modeling. Such approaches have been mainly focused on penalty based minimization and unmet demands. Barbarosoğlu and Arda (2004) and Salmerón and Apte (2010) propose models to minimize logistics costs and penalties due to unmet demands; while Lin et al. (2012) propose a model that considers penalties for late deliveries, and costs associated with inequality of services. To address the impacts on the beneficiaries, some

researchers suggested proxy measures for human suffering and the social implications of designing delivery strategies (Barbarosoglu et al. 2002; Tzeng et al. 2007; and Balcik et al. 2008) while other group uses priority factors to encourage the satisfaction of the most urgent needs (Özdamar 2004; Yi and Kumar 2007; Chang et al. 2007; Yi and Ozdamar 2007; Rawls and Turnquist 2010).

In a separate attempt away from optimization, Gralla et al. (2014) used Conjoint Analysis of experts' preferences to define an objective function able to assess the trade-offs among the goals to be pursued when deciding on relief distribution strategies. However, they concluded that results vary according to the weight given to the analyzed factors. Similarly, Gutjhar et al (2016) reviewed multicriteria optimization approaches in humanitarian aid and found that equity and fairness are concepts still missing in the literature and that even though they are somehow included in most recent publications, there is no agreement in how to evaluate it in the available objective functions. Overall, such approaches are inappropriate because they cannot correctly account for the complex non-linear effects associated with human suffering of the beneficiaries over time (Holguín-Veras et al., 2013).

To gain insight into how best to formulate the objective functions used in analytical models of post-disaster humanitarian operations, Holguín-Veras et al. (2013) used welfare economics to propose a social costs (SC) objective function. Such function includes the logistics cost associated with the relief distribution and the impacts of the relief effort on the beneficiaries. The impacts on the beneficiaries are measured using a deprivation cost function (DCF) that depends on the time the individual has no access to a good or service (called deprivation time). This function captures the opportunity cost perceived by the impacted population at a specific location when supplies are

distributed elsewhere. SC allow the decision maker to design a relief distribution strategy that accounts for the operational costs, the benefits of delivering the relief supplies, and the opportunity costs produced by the delivery strategy.

The DCF included in the social costs function is assumed a function of deprivation time, and the characteristics of the individual (e.g., age, gender, health condition). DCFs are monotonically increasing, non-linear, and convex with respect to deprivation time (Holguín-Veras et al. 2013). However, these functions depend on the good the individual is deprived of. Figure 1 shows the DCFs experienced by an individual due to the lack of access to different types of commodities (i.e. water and other basic supplies) under the same deprivation time. This indicates that a life sustaining supply like water may have a different (usually higher) deprivation cost compared to other supplies such as food.

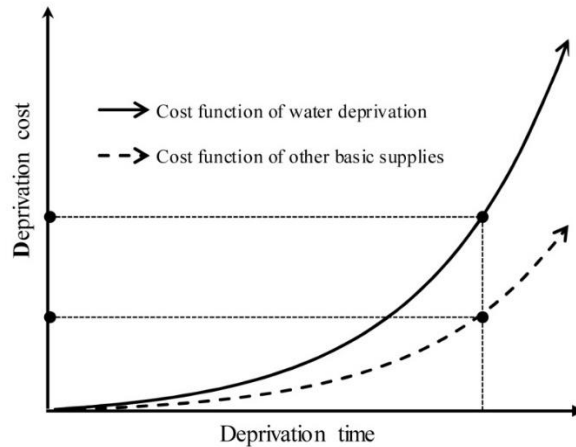


Figure 1. Deprivation Cost Functions

An important aspect of the DCF is that it is associated with non-additive demands. That is, individuals affected by long periods of deprivation do not require consuming the resources missed during the total shortage period when they finally get the assistance. (e.g. a person deprived of food for three

consecutive days, will not eat three days' worth of food when the supplies arrive).

Deprivation time, on the other hand, have negative impacts on the physical, emotional or mental integrity of the individual and they depend on the associated deprivation time. Since individuals affected by disaster experience consecutive cycles of deprivation, there is a possibility of experiencing residual effects (see Holguín-Veras et al. 2013), even though the adaptive nature of the human body. Long periods of deprivation can generate significant damage, affecting the chances of survival (Corning, 2000). Hence, value of life is considered the terminal point of a deprivation cost function (Holguin-Veras et al., 2016).

Very few publications have used deprivation costs in their models and all of them assume no residual effects on impacted population. Pérez and Holguín-Veras, (2015) developed a model that explicitly considers the effects of social costs in delivering supplies. However, the authors leave unaddressed questions regarding the methodology to estimate the deprivation costs element in the SC function. In response to these considerations, Holguín-Veras et al. (2016) estimated deprivation cost functions using contingent valuation (CV) techniques aiming to provide a consistent metric that could be explicitly incorporated into the models assessing the impacts of delivering critical supplies.

An alternative approach is to use the stated choice method that allows the direct inference of a value from the hypothetical choices through the tradeoffs that people make between the attributes of the choice set. This chapter proposes a novel methodology for valuing economic benefits and costs due to changes in welfare for the time spent to distribute critical supplies (i.e. water) in disaster

relief operations. The main principle is that there is an inverse relationship between the benefits perceived by the individuals with respect to deprivation time. That is, a larger waiting time for supplies is associated with lower social benefits. In consequence, a systemic reduction in the deprivation times, will lead to a higher perception of wellbeing in survivors. Deprivation costs perceived by individuals due to delays in relief distribution are higher than their logistics costs and such additional costs are not reflected in the market price of goods. Thus, they must be valued in monetary terms so the benefits for timely provisions are maximized. The next section describes the economic valuation techniques available to estimate such benefits.

2.2. Economic Valuation Techniques

Economic valuation is the process of estimating the value of a non-market good or service (Bateman et al. 2002). This field is relevant for this chapter because the impacts of aid distribution after disasters cannot be valued in a functioning market. In other words, these are economic externalities (Holguin-Veras et al., 2013). There are several methods for the valuation of externalities. Most of them are based on the use of preferences for estimating the needed values (Schipper et al. 2001; Bateman et al. 2002). Among those, one can find Revealed Preferences and Stated Preferences techniques. Revealed preferences (RP) techniques consist of collecting information about observed choices and decisions. The main strength of these surveys is its realism, since the data correspond to the actual behavior of the individuals. However, in terms of understanding individual's behavior, the technique has several limitations. It needs an observable market, data of observed choices may not provide the desired variability in the data, and it is not possible to collect information from individuals that have not experience the event before. These limitations would be surmounted with the design of real-life controlled experiments (Ortúzar and

Willumsen, 2011). In contrast, stated preference (SP) methods collect information about respondent's intention in hypothetical settings as opposed to their actual behavior as observed in real markets. SP techniques enable economic valuation through the willingness to pay for marginal changes in welfare due to the distribution of critical supplies. These techniques attempt to capture the behavior of individuals facing a set of choices in the absence of a market. The most popular SP methods are contingent valuation (CV), conjoint analysis (CA), and stated choice (SC) techniques (Ortúzar and Willumsen, 2011).

Stated Choice (SC) techniques are widely used, particularly for goods which are seldom traded or non-tradable in markets. Among other applications, they have been used successfully for environmental valuation (Rizzi et al., 2014; Hoyos, 2010;), valuation of moral goods (Johansson-Stenman and Svedsäter (2012), valuation of flood risk reduction (Reynaud and Nguyen, 2013), economic estimation of the value of life (Shah et al, 2015; Rizzi and Ortúzar, 2003), valuation of health programs (Louviere and Lancsar, 2009), and valuation of time (Ojeda-Cabral et al., 2015). Although SC experiments are controversial because of their hypothetical nature and the contested reliability and validity of their result, they remain useful for non-market valuation, though their results should be used with caution (Rakotonarivo et al., 2016). Particularly, in the case of social sciences, there are evidences about the high reliability of SC experiments, encouraging their use by private and public decision makers (Liebe et al., 2016).

Contrary to CV, SC technique does not directly ask respondents to state cost values in their answers. Instead, the values are estimated from the compensatory valuation of attributes that people make based on hypothetical choice scenarios. As a result, such values can be transferred among different

modeling scenarios (Morrison and Bergland 2006). Furthermore, the SC methods provide more information about the valuation of goods as it is possible to determine the subjective value of the attributes describing the choice alternatives. These attributes make SC methods a suitable tool for the valuation of non-market goods. A concern related to SP valuation techniques such as Stated Choice, is *hypothetical bias*, which states the difference between the preference and the actual behavior of the respondents. Different techniques have been proposed to minimize this bias. Cheap talk, developed by Cummins and Taylor (2009) is one of those. With this technique, respondents are explained the importance of providing responses as close as possible to their actual behavior and their impact in hypothetical bias. Although not perfect, the literature has shown that this technique is effective in minimizing this bias (Champ et al., 2009; Bosworth and Taylor, 2012; Loomis, 2014).

Although economic valuation techniques have been widely used in many fields, there is not much development in its uses on analytical models for disaster response operations. Besides Holguin-Veras et al. (2016), there is no other study of this kind. However, their use of contingent valuation makes their experimental design and objective different to the one proposed here. This chapter, in contrast, is a stated choice approximation of the economic impacts of relief distribution using a more elaborated experiment.

A few key observations are worth mentioning about the literature reviewed in this section. First, it is important to assess the impacts of relief distribution after disasters. Second, there is a large body of research on operations management to support the decision making process to be performed in disaster response. However, there is not enough literature aiming to assess the economic impacts of relief aid distribution. Third, there is no previous literature that combines stated choice methods with ex-ante remedial measures to minimize

hypothetical bias in an empirical setting. The next section describes the proposed model along with its econometric foundation.

2.3. Description of the Methodology to Estimate DCFs

When a disaster strikes an area, impacted individuals are left with reduced or no access to critical supplies. As the relief effort begins, people decide to wait until the help arrives or move to another place looking for supplies to survive. In such decision-making process, affected people try to maximize their wellbeing subject to certain socioeconomic restrictions. In microeconomic terms, that is a utility maximization problem in which people try to make decisions in an unusual context that allow them to reach the maximum level of satisfaction. In that context, a new approach is presented to estimate the economic impacts of relief distribution. In this chapter, the estimations are based on Random Utility Models (RUMs), popular in other fields such as marketing and which flexibility allow its use in disaster response. The following sections provide specifics about the use of these models in the proposed research.

2.3.1. Notation

The notation used in the proposed formulations is described below.

J	Set of available alternatives of choice.
U_{nj}	Level of utility that the individual n obtains from alternative $j \in J$.
V_{nj}	Systematic utility that the individual n obtains from alternative $j \in J$.
ε_{nj}	Random error term, which captures the combined effect of the different factors that introduce uncertainty into choice modeling.
\mathbf{X}_{nj}	$(1 \times K)$ vector of attributes of alternative j as faced by individual n . The K^{th} attribute is the deprivation time, then $x_{njK} = t_{nj}$

DT_{nj}	Deprivation time related attribute of the alternative j as faced by the individual n .
S_n	Vector of socioeconomic characteristics of the individual n .
ASC_j	Constant that is specific to alternative j , which captures the average effect on utility of all factors that are not included in the model.
CS_n	Consumer surplus (or utility in dollar terms) that the person n receives in the choice situation.

2.3.2. Economic Foundation

For the econometric estimations, this research uses Random utility-based Discrete Choice Models (DCMs), in which the individual expresses its preferences by selecting one alternative from a set of available choices. To collect such data stated-choice (SC) experiments are used. This method consists of a set of hypothetical choice scenarios. In each scenario, respondents are asked to choose their preferred alternative from amongst the total number of hypothetical alternatives constructed by the analyst, after evaluating their attributes. Each individual is assumed to have preferences for such attributes, and preferences can vary across individuals in a compensatory way. That is, individuals would obtain a certain level of utility from each alternative j , choosing the one that maximizes their personal utility U_{nj} (McFadden 1973; Williams 1977; Train 2009; Ortúzar and Willumsen 2011).

The maximum utility an individual can achieve if an alternative is chosen is known as the conditional indirect utility function. Although the modeler has knowledge of the attributes for the different alternatives, it does not have complete information of all the factors pondered by the individual at the time a choice is made. In that context, the analyst assumes that the individual's utility is formed by two elements (see Equation 1): an observable component

or systematic utility function, V_{nj} , and a random error term, ε_{nj} , which reflects any observational errors made by the modeler (McFadden 1973; Williams 1977).

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad (1)$$

The systematic utility (V_{nj}) is a function of the measurable attributes of both, the alternatives (X_{nj}) and the individual (S_n). Depending on the assumptions regarding the distribution of the random error component, different formulations arise. For instance, if the error terms distribute independently and identically (iid) Gumbel, the multinomial logit model (MNL) arises (Train 2009). The specification of the systematic utility function is frequently assumed to be linear in the parameters as shown in Equation 2. However, it is not always appropriate in all modeling contexts.

$$V_{nj} = ASC_j + \sum_{k=1}^K \beta_{njk} x_{njk} \quad (2)$$

The term x_{njk} represents the attribute k of the alternative j that the individual n observes, whereas β_{njk} is the parameter to be estimated, which may differ among the individuals. In such specification, these parameters represent the marginal utility derived from the attributes of the alternatives (e.g. cost, deprivation time). The parameter ASC_j represents the constant that captures the effect of all factors that have not been included in the model. For identification issues one of them must be fixed to zero.

Although MNL is the most popular discrete choice model, it is limited by certain restrictive assumptions, such as the total absence of heterogeneity in the preferences; consequently, the implicit assumption is that preferences are

identical among all the individuals ($\beta_{njk} = \beta_{jk}$). This restriction does not allow the modeler to know the influence of the socioeconomic characteristics (e.g. gender, age, family size, income) on the individual's willingness-to-pay (WTP). However, with a correct specification, it is possible to represent the systematic variation of tastes, which is defined as the valuation that people, gives to certain attributes of the choice set. In order to account for these variations in the model, it is necessary to rewrite Equation 2, by defining the coefficients of each attribute as an interaction with the individual socioeconomic characteristics S_n ; that is:

$$V_{nj} = ASC_j + \sum_{k=1}^K (\beta_{jk} + \sum_{l=1}^L \delta_{jkl} s_{nl}) x_{nj k} \quad (3)$$

Where s_{nl} is a variable related to the socioeconomic characteristic l of individual n (e.g. gender) and δ_{jkl} is a parameter that accounts for the interaction between the attribute $x_{nj k}$ and s_{nl} . This equation states that given the characteristics of the individual, different marginal utilities are obtained for a given attribute. Note that the same socioeconomic variable can appear in the expression corresponding to each coefficient. The taste parameters (δ_{jkl}) depend on the individual characteristics in a deterministic manner (Ortúzar y Willumsen 2011).

Using discrete choice models is appropriate for the purpose of this chapter as they allow the assessment of changes in the utility for the affected individuals due to deprivation time. To do that, it is necessary to develop an experiment where the individual is presented with the alternatives of buying or not critical supplies under different conditions of price, budget, and deprivation time. In consequence, a systematic utility function can be specified (V_{nj}) including the

effects of attributes related to the individuals' welfare and of the deprivation time. In the model specification, the non-linear nature of the cost associated to the individual's deprivation must be considered. This nonlinear effect is obtained by specifying a functional transformation (f) on the deprivation time attribute as shown in Equation 4.

$$V_{nj} = ASC_j + \sum_{k=1}^{K-1} \beta_{jk} x_{nj k} + \beta_{jt} f(DT_{nj}) \quad (4)$$

And considering the systematic variations effects, this utility function becomes

$$V_{nj} = ASC_j + \sum_{k=1}^{K-1} \beta_{jk} x_{nj k} + (\beta_{jt} + \sum_{l=1}^L \delta_{jtl} s_{nl}) f(DT_{nj}) \quad (5)$$

This transformation captures the variations on the WTP due to deprivation time as well as the systematic variation resulting from the socioeconomic characteristics of the individuals. Although it may be argued that the exponential function is probably adequate in this context, the use of statistical transformations, such as the Box-Cox method, enable the modeler to explore other appropriate functional forms (Gaudry and Wills 1978; Ortúzar y Willumsen 2011). The Box-Cox transformation of a positive variable x is given by:

$$x^{(\varphi)} = \begin{cases} \frac{(x^\varphi - 1)}{\varphi}, & \text{if } \varphi \neq 0 \\ \log(x), & \text{if } \varphi = 0 \end{cases} \quad (6)$$

The Box-Cox transformation is continuous for all values of φ . Note that if $\varphi = 1$, it reduces to the linear form; furthermore, if all $\varphi = 0$ the log-linear form is obtained (Ortúzar y Willumsen 2011).

The parameters of the utility function (i.e. β, δ, φ) can be estimated with the information collected in SC surveys. Regarding the parameter estimation process, the maximum likelihood (ML) method is used in this research. Though alternative procedures for estimating discrete choice models have been developed within the Bayesian tradition (Train, 2009). Additionally, ML is based on the idea that although a sample could originate from several populations, a particular sample has a higher probability of having been drawn from a certain population than from others. Therefore, the maximum likelihood estimates are the set of parameters that makes the observed data the most probable (Ortúzar y Willumsen 2011).

The individuals whose willingness to pay for access to a particular type of good or service is greater than or equal to its current price, will buy it. This transaction improves the individual's welfare (Eshet et al. 2006). The same is also known as the consumer surplus (CS) and defined as the utility, in monetary terms that a person receives in a choice situation. In this research, changes in the individual's benefits due to time spent waiting for water provision are measured by the variation in consumer surplus.

For an individual n , consumer surplus is

$$CS_n = \left(\frac{1}{\alpha_n} \right) \max_j (U_{nj}) \quad (7)$$

where α_n is the marginal utility of income. That is, $\alpha_n = \partial U_n / \partial I_n$, with I_n the income of individual n (Williams 1977; Train 2009). Typically a price or cost variable enters the representative utility, in which case the negative of its coefficient is α_n .

As the modeler only knows the systematic utility V_{nj} , and the distribution of the associated errors, then it is possible to calculate the expected consumer surplus as follow:

$$E(CS_n) = \frac{1}{\alpha_n} E[\max_j (V_{nj} + \varepsilon_{nj})] \quad (8)$$

If errors are IID Gumbel, then this expectation becomes Eq. (9) (Williams 1977; Small and Rosen 1981).

$$E(CS_n) = \frac{1}{\alpha_n} \ln \left(\sum_{j=1}^J e^{V_{nj}} \right) + C \quad (9)$$

Where the expression in parentheses is the denominator of the logit choice probability model, which is often called the *log-sum* term and C is a constant that, according to Train (2009), is irrelevant from a policy perspective and can be ignored. In consequence, the economic benefits of humanitarian relief distribution after disasters can be estimated as the total change in consumer surplus that results from a change in deprivation time experienced by the individuals receiving humanitarian aid. In particular, $E(CS_n)$ is calculated before (⁰) and after (¹) the aid distribution takes place, as shown in Equation 10.

$$\Delta E(CS_n) = \frac{1}{\alpha_n} \left[\ln \left(\sum_{j=1}^{J^1} e^{V_{nj}^1} \right) - \ln \left(\sum_{j=1}^{J^0} e^{V_{nj}^0} \right) \right] \quad (10)$$

It is highlighted that when a disaster occurs, the utility is a decreasing function with respect to time without access to basic goods. Consequently, the variation in consumer surplus is negative as time increases, which becomes a deprivation cost.

Figure 2 illustrates this econometric approach and shows the relationship between DCs and the benefits (B) that individuals perceive after a deprivation time, t_a . In this case, the affected population can only withstand a maximum deprivation time, T_{max} . If individuals are immediately served after the event occurs, the deprivation time will be null; in such case, he/she will receive the maximum benefit from the response process. In other words, the DCFs represent the economic loss of benefit or welfare changes experienced by individuals. This approach is consistent with the concept of externalities (Brey 2009).

This economic foundation provides with the tools to implement the methodology to the disaster context. The next section presents the data collection effort and the descriptive analysis of the sample.

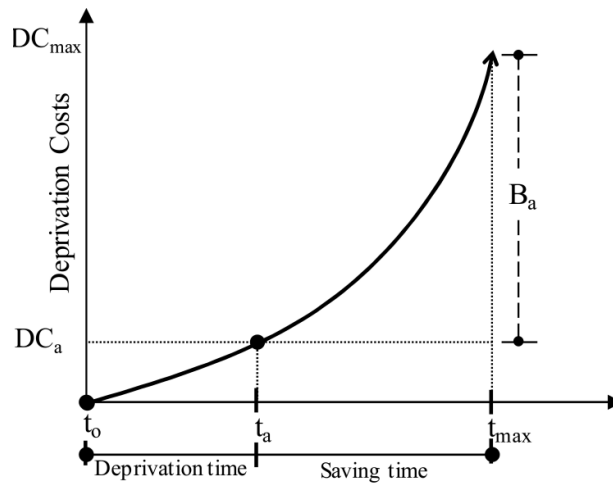


Figure 2. Relationship of deprivation costs/benefits

2.3.3. DCFs and Latent Variables in Disaster Contexts.

The econometric formulations of DCFs presented previously did not include latent variables (LVs) of individuals, which allow knowing how individuals' attitudes and perception influence their behavior at the time to make a decision to achieve a better level of welfare (Holguín-Veras et al. 2016). The people's experiences of disasters make them uniquely aware of their vulnerability, which in turn can positively influence their risk perception as well as their preparedness behavior (Peacock et al. 2005). In this sense, the knowledge of how individuals with different socioeconomic characteristics and risk perceptions value the DT is a critical issue since it could lead to more accurate measurements of the economic impact of humanitarian aid operations.

The economic valuation of LVs in disaster contexts also allows knowing the social costs associated with the physiological suffering of people, which are a consequence of the event itself (Parker et al. 1987; Rose and Lim 2002; van der Veen 2004). These costs are an externality derived from the disastrous events and the humanitarian aid distribution strategies (Gutjahr and Nolz (2016); Holguín-Veras and Jaller (2011); Hu and Sheu (2013); Sheu (2007).

In sum, it is convenient to estimate DCFs including LVs to know the influence of people attitudes and perceptions on the individual disaster preparedness as well as the interaction of these psychosocial factors with their socioeconomic characteristics. Also, recognizing the role of psychosocial factors is fundamental in public campaigns aiming to promote individual disaster preparedness (Hoffmann and Muttarak 2015).

2.3.4. Modelling with Latent Variables

In addition to the econometric foundation presented in section 2.3.2, the evaluating of non-observable psychosocial factors in the decision-making

process of selecting a logical choice from a set of available options, the literature has shown remarkable developments. The most relevant are the use of LVs into the specification of econometric models, which allow explaining the choice process in a more realistic way (Walker 2001).

LVs can be modeled using a structure with two components: (1) the structural equations, which relate the people's socioeconomic characteristics (\mathbf{S}_n) with the LVs (\mathbf{Z}_n^*) (Equation 11) and (2) the measurement equations, which relate the indicators of people's perceptions (\mathbf{I}_n) with the LVs at the same time (Equation 12) (Walker 2001). This is currently known in the scientific literature as the Multiple Indicators Multiple Causes (MIMIC) model.

Due to the ordinal nature of the observed indicators, the measurement equations are specified as ordinal logit models. When indicators are categorical variables, the measurement equations can be estimated according to Equation 12 and Equation 13. If the categorical indicators are defined, the vector of thresholds ($\boldsymbol{\tau}$) must be specified among which a continuous latent variable will take some value from the categorical indicator. For each indicator, if there exist K categories, it is needed to estimate $K-1$ thresholds.

$$Z_{nl}^* = \lambda_l \mathbf{S}_n + \omega_{nl} \quad (11)$$

$$I_{nm} = \gamma_m \mathbf{Z}_n^* + u_{nm} \quad (12)$$

$$I_{nm}^* = \begin{cases} 1 & \text{if } \tau_{0m} < I_{nm} < \tau_{1m} \\ 2 & \text{if } \tau_{1m} < I_{nm} < \tau_{2m} \\ \dots & \dots \\ K & \text{if } \tau_{K-1m} < I_{nm} < \tau_{Km} \end{cases} \quad (13)$$

\mathbf{Z}_n^* is a vector of latent variables.

\mathbf{S}_n is a vector of socioeconomics and personal characteristics of the individual n and his/her household.

ω_{nl} is an error term. It is supposed that it distributes Normal, with mean 0 and variance $\sigma_{\omega_l}^2$. For identification, the variances were set to one ($\sigma_{\omega_l}^2=1$) for each latent variable $l=1,...,L$.

I_{nm} is the continuous indicator m .

I_{nm}^* is the categorical indicator m .

u_{nm} is an error term. It is supposed that it distributes logistic, with mean zero and scale parameter $\delta_m = \pi/\sqrt{3} \sigma_m$. For identification issues, this parameter was fixed $\delta_m = 1$.

λ, γ are vectors of parameters to be estimated.

If F is the cumulative distribution function, the probability of observing I_{nm} within a discrete indicator or category k , can be written as Equations 14 and 15 if the error distributes logistic. The set of thresholds τ must be estimated. For identification are fixed $\tau_{0m} = -\infty$ and $\tau_{Km} = +\infty$.

$$P\{I_{nm} \in k | \mathbf{Z}_n^*\} = F(\tau_{pk} - \gamma_m \mathbf{Z}_n^*) - F(\tau_{p(k-1)} - \gamma_m \mathbf{Z}_n^*) \quad (14)$$

$$P\{I_{nm} \in k | \mathbf{Z}_n^*\} = \frac{1}{1 + e^{-(\tau_{km} - \gamma_m \mathbf{Z}_n^*)}} - \frac{1}{1 + e^{-(\tau_{(k-1)m} - \gamma_m \mathbf{Z}_n^*)}} \quad (15)$$

The incorporation of LVs into the utility function (U_{nj}) of the DCMs conforms HLVD CMs as in Equation 16. Figure 3 also illustrates the general structure of the HLVD CMs (Bolduc and Alvarez-Daziano 2010; Walker and Ben-Akiva 2002).

$$U_{nj} = ASC_j + \beta X_{nj} + f(t_{nj}, \beta_t) + \alpha Z_{nj}^* + \varepsilon_{nj} \quad (16)$$

Where:

ASC_j is the alternative specific constant that captures the average effect in the utility of all non-included factors of the alternatives in the modeling

X_{nj} is a vector of attributes of the alternative and socioeconomics variables, excluding DT.

β, α are vectors of parameters to be estimated.

$f(t_{nj}, \beta_t)$ is a functional transformation on the DT attribute t_{nj} . β_t are the parameters of the function. Considering the non-linear and convex nature of the DCFs, the Box-Cox and exponential transformations for DT will be specified.

It is supposed that the error terms ε_{nj} are independent and identically distributed Gumbel.

The individual choices, given the choice set J , were expressed as a function of the utilities according to (17).

$$y_{nj} = \begin{cases} 1 & \text{if } U_{nj} \geq U_{ni}, \forall j \in J \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

The unknown parameters can be estimated with simultaneous estimation by the simulated maximum likelihood technique, building a joint likelihood function that includes the MIMIC model and the DCM. The joint estimation of the LVs and the random utility model is a more appropriate approach because it provides a more consistent estimation (Raveau et al. 2010).

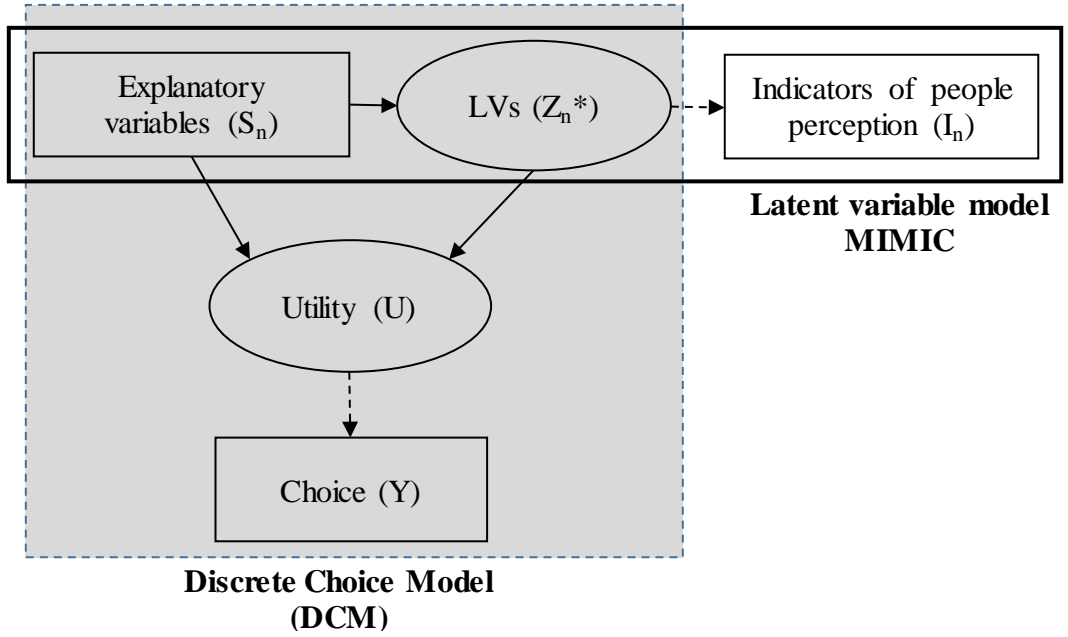


Figure 3. HLVDCMs structure

2.4. Vulnerability in Transportation Networks

Consistent with Cantillo et al. (2016a); Holguín-Veras et al. (2016); Holguín-Veras et al. (2013); Pérez and Holguín-Veras (2015) humanitarian logistics operations must be coordinated and planned considering total social costs (SCs), which include the logistics and deprivation costs. Further considering that these costs occur simultaneously during the execution of the humanitarian logistics operations, and the latter are of greater importance during the post-disaster response phase. Moreover, transportation networks are a key supporting system for the design and implementation of an effective, efficient and socially optimal distribution strategy. However, these disasters and other factors may impact the vulnerability, accessibility, and resilience of such networks.

2.4.1. Vulnerability

Vulnerability is a factor of inherent risk in a system exposed to threats. It is also an intrinsic predisposition to be affected or to suffer any damage (Berdica 2002; Cardona 2001). There is no exact definition for the term vulnerability; thus, it could be defined in many ways (Balijepalli and Oppong 2014), either in terms of connectivity (Di Gangi and Luongo 2005), accessibility (Berdica and Eliasson 2004; Bono and Gutiérrez 2011; Jenelius 2009; Jenelius 2010; Jenelius and Mattsson 2012; Jenelius et al. 2006; Sullivan et al. 2010; Taylor and Susilawati 2012), serviceability (Berdica 2002), efficiency (Chen et al. 2012; Qiang and Nagurney 2008), and unmet demand (Qiang and Nagurney 2012). In turn, Agarwal (2011) defined vulnerability as the susceptibility that a system has to a kind of damage or adverse events due to its form and characteristics. Meanwhile, Freeman et al. (2008) refer to transportation vulnerability as the susceptibility to interruption or degradation on the network that would significantly reduce the efficiency or operating capacity. Jenelius et al. (2006) and Chen et al. (2007) interpret it as the susceptibility of the transportation system to incidents that can significantly reduce the services offered to the network users. Berdica (2002) and Zhixin et al. (2010) consider that the term vulnerability refers to the fragility of networks to incidents that can significantly reduce their serviceability. Generally speaking, most researchers agree that this is a measure of the network susceptibility to adverse events. Perhaps the definition that comes closest to the purpose of this research is expressed by Taylor and D'Este (2005), who indicated that a network is vulnerable if the loss or degradation of a small number of links or routes significantly decreases the accessibility to the destination nodes.

In most cases, it is almost impossible or very difficult to avoid a threat; it is only possible to reduce (mitigate) the vulnerability of the exposed elements

(Cardona 2001). The first step in this direction is the identification of critical infrastructure (e.g., links and nodes) where a possible failure could trigger a greater effect for the whole network (Zhixin et al. 2010), and planning actions to reduce the impact (Chen et al. 2012; Nagurney and Qiang 2009).

Using indicators is a frequent practice when assessing vulnerability in transportation networks. The literature concentrates on two main types of indicators: those taking into account the operations of the transportation system (e.g. flows), and those that only focus on the topological characteristics of the network (e.g. distance, travel time).

Table 1 summarizes the main features of different models for the analysis of transportation networks vulnerability. It shows that the most common indicators (methodologies) relate to the minimization of logistic costs (mainly transportation-related) and the effects of traffic congestion. The review shows that total SCs have not been considered, which undoubtedly reflects the models' commercial logistic roots and the fact that post-disaster humanitarian logistics modeling is still in early stages of development. Clearly, measuring the network vulnerability based on commercial logistics does not lead to an optimal social outcome as the suffering brought about by the delays in the provision of basic supplies is not internalized by the beneficiaries of the aid.

Additionally, the link cost in most of the current approaches is a function of its flow. These formulations assume additive and flow-independent link costs; thus, the route cost from an origin to a destination is the sum of each individual link cost. However, including deprivation costs requires a more general expression for estimating the total route cost because deprivation costs are not additive with each link.

Table 1. Vulnerability analysis models of transportation networks

Author (s)	Single link (S) / Multiple (M)	Method	Approach
Balijepalli and Oppong (2014)	S	UE	Flow
Chen et al. (2007)	S	ME	Generalized cost
Chen et al. (2012)	S	UE	Inverse of time
Wang et al. (2016)	M	UE	Travel time
Gómez et al. (2011)	S	Min TC	Generalized cost
Jaller et al. (2015)	S	UE	Travel time
Jenelius (2009)	S	UE	Travel time
Jenelius (2010)	M	UE	Redirected flow
Jenelius and Mattsson (2012)	M	UE	Travel time
Jenelius et al. (2006)	S	UE	Generalized cost
Lu et al. (2014)	S or M	UE	Travel time
Luathep et al. (2013)	S	UE	Generalized cost
Nagurney and Qiang (2009)	S or M	UE	Travel time
Rodríguez-Núñez and García-Palomares (2014)	S or M	UE	Travel time
Qiang and Nagurney (2008)	S	UE	Flow/shorter distance
Qiang and Nagurney (2012)	S or M	Min TC	Generalized cost
Rupi et al. (2015)	S	UE	Flow
Scott et al. (2006)	S	UE	Travel time
Sohn (2006)	S	UE	Distance and flow
Sullivan et al. (2010)	S	UE	Travel time
Taylor (2008)	S or M	UE	Benefits
Taylor and D'Este (2005)	S	SP	Inverse of the distance
Taylor et al. (2006)	S	UE	Generalized cost
Zhixin et al. (2010)	S	UE	Time x distance

UE: user equilibrium; ME: Market equilibrium; TC: Total Costs; SP: Shortest path

Generally, the current methodologies analyze vulnerability by comparing system performance before and after the disruption and identifying the most critical links in the system (Bíl and Vodák 2014; Luathep et al. 2013).

Taking as starting point the idea of physical infrastructure, it is important to highlight that vulnerability as an internal risk factor must also relate to social susceptibility and the communities' capabilities to absorb the impact or disruption (Cardona 2001). Obviously, the greater the number of people in a vulnerable situation, more critical the access routes are to such population. According to D'Este and Taylor (2003), a node (populated center) is vulnerable if the degradation of one or more routes on the network significantly decreases the node accessibility; then, the lack of access to the affected area would suddenly increase the SCs. In that sense, it is necessary to develop a model for assessing the vulnerability of transportation networks considering the effect of SCs. This would allow assessing the level of importance that each network's link has for the access of humanitarian operations to areas hit by disasters.

2.4.2. Accessible and Resilient Transportation Networks

Accessibility is frequently linked to the concept of vulnerability (Chen et al. 2007). This close relationship makes vulnerability to be so-called a "reduced accessibility" (Rodríguez-Núñez 2012). In general, accessibility refers to the ease of achieving a service or reaching a particular place (Bono and Gutiérrez 2011). In most cases, accessibility is measured from an origin node, considering the ease of connecting with other destination nodes (Páez et al. 2012). According to Berdica (2002), an increase in the number of alternative routes of a transportation service or an increase in the number of services along a certain route are aspects that assume an increase in the accessibility of users to develop their activities.

Accessibility can also be used to assess the importance of particular links to a transportation network. If the disruption of a link, a_1 , on the network induces greater loss of accessibility to users than another link, a_2 , then a_1 is more

significant than a_2 and therefore must be primarily intervened (Luathep et al. 2013; Sohn 2006).

Considering that after extreme events some places are less accessible than others (Balijepalli and Oppong 2014; Bono and Gutiérrez 2011), the concept of accessibility arises as an important indicator of the transportation network performance (Páez et al. 2012). Therefore, accessibility is vital after the occurrence of a natural disaster (Lu et al. 2014; Sohn 2006), especially to ensure the distribution of essential supplies and subsequent post-disaster restoration.

On the other hand, the concept of resilience was introduced in the context of ecological systems subject to external influence (Holling 1973). It was initially defined as a measure of the persistence of systems and of their ability to absorb changes and disturbances, adapting to the dynamics of the environment (Agarwal 2014). Other researchers defined it as the capacity of a system to return to its original state after being disturbed by an external force (Berdica 2002; Lee et al. 2014). Although the definition continues to evolve and receive different interpretations, conceptually, it has an opposite meaning to vulnerability (Schreiner 2013).

In transportation networks, resilience is the ability to continue working with some acceptable level of service after a disruption (Rodríguez-Núñez and García-Palomares 2014), or capacity to withstand the forces of an extreme event (Lee et al. 2014; Schreiner 2013). Figure 4 illustrates the recovery process of a system after a sudden and partial loss of functionality. This recovery depends on the number of connections that constitute the specific system and how the system components are connected. It is important to note

that, depending on the adopted definition, the system could be restored to its original full functionality, a partial state, or even a different system state.

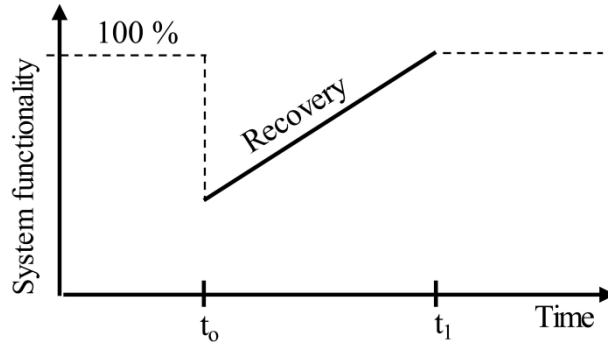
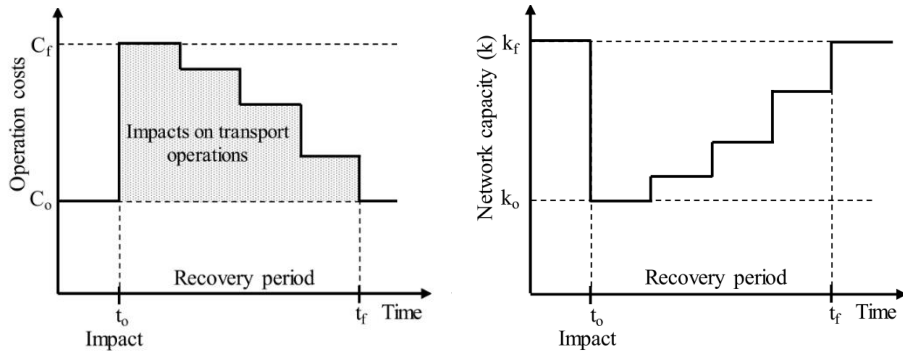


Figure 4. Recovery of a system

In general, disruption of one or more links on a network could lead to losses in its capacity and also the increase of operating costs (See Figure 5), which progressively reduce depending on the recovery activities. The recovery cost (RC) is an essential component for assessing resilience (Yu et al. 2015) and is the sum of the derivative cost from the system impacts (SI), i.e., perceived costs due to the affectation of the system, plus the total recovery effort (TRE), i.e., private costs recovery. Large RCs require greater efforts and time for recovering, affecting the resilience of the system.

DCs can be approximated to the SIs, while the LCs from a disaster response operation constitute the TREs. Thus, the RC is a social cost resulting from the impact on the system, and improving the accessibility of humanitarian operations to affected areas can minimize it.



a. Impact on system operation

b. System recovery

Figure 5. Impact and recovery in the transportation system

3 ASSESSING ECONOMIC IMPACTS OF HUMANITARIAN RELIEF DISTRIBUTION

3.1. Introduction

As explained before, individuals who have to wait longer times in receiving life-sustaining items experience negative changes on their personal utility. These changes in personal utility expressed in monetary units are a good estimation of deprivation costs. Therefore, it is critical that humanitarian aid operations develop appropriate approaches for estimating these costs that support effective allocation of resources. To this effect, this chapter uses the methodology proposed in section the 2.3 to estimate costs and benefits resulting from relief distribution efforts during the response to a disaster. The approach considered in this chapter uses Stated Choice (SC) techniques to estimate econometric models based on individuals' discrete choices. The model results are used to evaluate the monetary value of deprivation due to the lack of access to water in the immediacy of a disaster. The models developed can be incorporated into comprehensive humanitarian logistics models to perform risk analysis as well as to conduct economic evaluation of humanitarian aid operations.

This chapter is organized as follows: In Section 3.2 applies the research methodology proposed in the section 2.3 using a sample from the Colombian Caribbean Region. Section 3.3 presents the models specification. In section 3.4 the models results and their corresponding analysis are presented. Finally, the chapter is concluded in Section 3.5.

3.2. Experimental Setup I: Providing Drinking Water as a Scarce Supply

In order to analyze the impacts of relief distribution, it is necessary to select a good that is critical for disaster response operations while, at the same time, it is easy to identify by the individuals taking the survey. After considering several alternatives, the authors decided to use drinking water. During humanitarian crises most of affected population need humanitarian assistance, particularly supplies to meet their essential needs. Such supplies cover an enormous spectrum, from medicines and food to shelter and tools. The provision of water is critical to preserve life in an emergency and has been recognized as an intervention of paramount concern to government and humanitarian organizations.

The data used in this chapter were collected through a Stated Choice (SC) survey that was applied to people randomly selected from six locations of the Colombian Caribbean region that have been subject to periodic floods and mudslides resulting from the rainy season in the country during the years 2010 and 2011. The breakdown of the sample by location is as follow: Barranquilla (38%), Cartagena (17%), Guamal (17%), El Piñón (17%), Ciénaga (8%) and Plato (3%). Figure 6 shows the map of the towns (in red) were the surveys were conducted compared to the impacted zones in the region. The sample includes people who had been previously impacted by a disaster; and people who had not been impacted. The former were obtained from a database from the Office of Prevention and Disaster Response (Unidad Nacional para la Gestion del Riesgo de Desastres- Colombia, 2012), the disaster response agency in the country. The latter were randomly selected from sectors not impacted by the events. All interviews took place face-to-face.

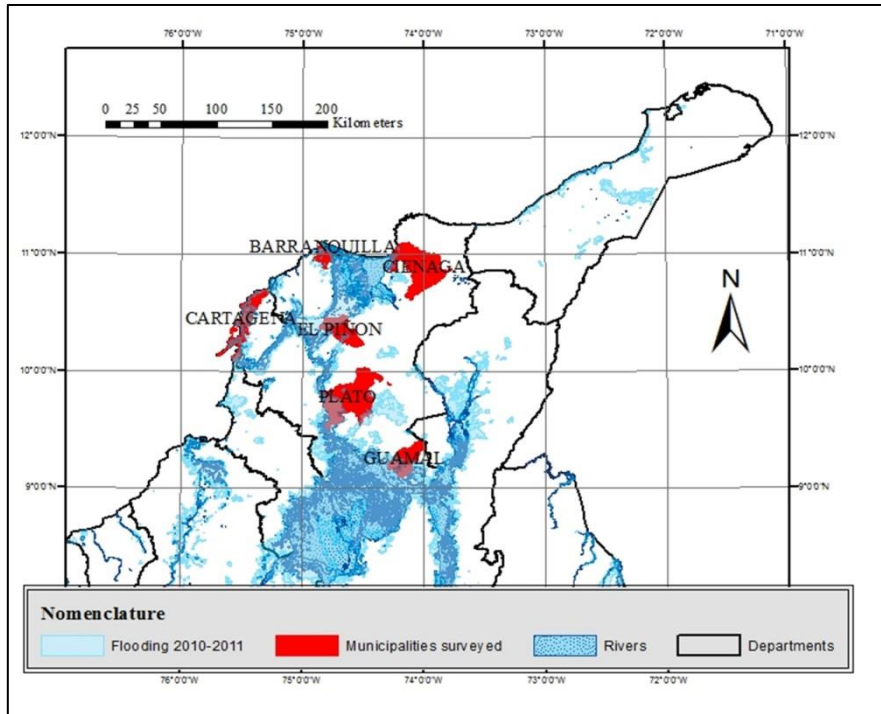


Figure 6: Study Area in the Colombian Caribbean region

The experimental variables used include: deprivation time (DT), time elapsed since last water consumption; waiting time (WT), additional waiting time to receive the water for free; budget (B), available amount of money in their pockets at the moment; the amount of water (in liters) available for purchase; and the total price of the purchase (P). The scenarios asked the respondents to choose between buying at certain price or wait additional time until the help arrives so it received water for free. In the design, it was important to include the variable Budget to eliminate a distorting effect generated by income or ability to pay. Since the intention is to recreate a condition after disasters, the survivor only has what is available in their pockets as banking systems usually do not work after this type of events.

Ten hypothetical choice scenarios were presented to respondents. Every situation includes a specific amount of water along with its price. The respondent was presented with the following hypothetical situation:

“Imagine that a disaster has occurred in the city where you live and that you have lost your possessions. No water or food is available and this situation will continue for at least several days. A few hours have elapsed and the only money available is what you have in your pockets. We are going to show you ten choice situations where you need to decide whether or not to purchase water for your own consumption at the given price.”

In addition, the respondents were read a Cheap-Talk script emphasizing the importance of getting accurate data to improve disaster response efforts. The text included was:

“The experience with other similar surveys indicates that people generally respond in one way but, in real life, may do something else. It is very common for a respondent to state their willingness-to-pay for water, but exhibit a different willingness-to-pay in real life. Please, when responding to the scenarios, try to guess what you would actually do. Please help us develop better response procedures by closely paying attention to the scenarios presented before giving an answer.”

The survey was structured in two sections. The first, gathered socioeconomic information of the respondent and its household, (e.g., age, gender, education level, occupation, household size, income level, children in the household). The second section contains the SC experiment previously described, which allows us to generate a hypothetical market. A total of 240 complete responses were collected.

If the respondents choose to purchase the amount of water, given a certain DT, then money available (i.e. their Budget) would reduce and that could prevent

them from covering other essential needs (e.g. food, medicine, transportation, communications). However, if the respondents want to keep the money available and cover their needs for water later on, then they have to wait an additional time until the humanitarian assistance arrives and distribute the water for free. In this context, the purchasing option is associated with the current time without access to supplies (*DT*), while the waiting option is associated with an expected deprivation time (*EDT*) until the arrival of the humanitarian assistance ($EDT = DT + WT$). The longer the *DT*, the more difficult it becomes for the respondents to imagine the realities of the scenarios, and the less reliable their responses become. This is the reason why the range of values of *DT* was assumed to be from 6 to 24 hours in the experimental design. The ranges of values considered were: Deprivation Time and Waiting Time from 6 to 24 hours, respectively. Budget from COP 50,000 to COP 200,000. Amount of water from 2.5 to 6 liters, and Price of water from COP 7,500 to COP 72,000. Details of the variables are shown in Table 2.

Table 2: Variables in Experimental Design

Variables	Values	
Current Deprivation time-DT (hr)	6, 12, 18, 24	
Waiting time-WT (hr)	6, 12, 18, 24	
Budget-B (COP)	50,000, 100,000, 150,000, 200,000	
Amount of Water Available for Purchase (L)	2.5, 4.5, 6	
Price of the purchase-P (COP)	For 2.5 L	7,500, 19,000, 30,000
	For 4.5 L	13,500, 34,000, 54,000
	For 6.0 L	18,000, 45,000, 72,000

Note: US \$1 = COP 2,000 approximately when the survey was applied

An important aspect is the selection of the range of the values of the experimental variables. The range of values of deprivation time could be from zero (no deprivation) to any time. Inclusive the moment at which the individual dies. However, an experimental design involving data for the entire range may

not be suitable as individuals may struggle to think of being long periods of deprivation. In the design, the values of deprivation (including the waiting time) range from 12 to 48 hours.

A factorial fractional design was used to create the set of scenarios to be presented to each respondent. The choice set was split into four blocks with ten situations. Each respondent was presented with one of these blocks from which it had to select its preferences. The design ensures balanced attributes and choices within each block (Louviere et al. 2000).

The data were post-processed, coded in an electronic data set, cleaned, and reviewed to ensure they represented the respondents' answers. The Price provided by the respondents, originally in Colombian Pesos (COP), were converted to US dollars (\$) using an exchange rate of COP 2,000 per \$1 (Banco de la República, 2015). A descriptive analysis was conducted to characterize the sample. See Table 3.

Using Budget as an experimental variable helps to remove the income effect from the responses as the scenario makes clear that the only money available to the respondent is the budget specified. In consequence, the available budgeted for other needs (AB) was treated as the difference between the budget (B) and the total price of the purchase (P). Individuals must respond based on the given scenarios and not on their own socio-economic condition.

The data show that the information collected belong to people aged between 15 and 78 years, out of which 48.3% were men and 51.7% were women. The respondents were independent people and heads of families. Many of them (45%) were people affected by floods between 2010 and 2011.

The sample included individuals representing a wide range of socio-economic conditions. The average age is 38 years and the average household size is 5

persons. The proportion of respondents with children (12 years or younger) is 46% and the proportion of respondents with adolescents between 13 and 17 years old was 46%. The proportion of respondents with low income level was 61% and with medium income level was 21%, according to the stratification system defined by the national government (DANE, 2016). A more detailed description of socioeconomic characteristics of the sample is presented in Table 3.

Regarding the hypothetical choice scenarios presented to respondents, 38% of male and 37% of female chose the purchase option whereas 11% of male and 14% of female were willing to wait for free humanitarian aid. In terms of employment, 38.75% of the individuals were employees in formal businesses; 21.67% of the sample were independent, mostly in the informal sectors of the economy; 21.25% stayed at home; and 12.5% were students. The average annual income reported was COP \$700.000 (US \$350), equivalent to 1.5 times the minimum wage at the time of the survey. The descriptive analyses indicate that the data provide a consistent representation of the population (DANE, 2016). The modeling effort is reported in the next section

Table 3: Summary Statistics

Gender		Average age by gender	
Male	48.33%	Women (years)	36
Female	51.67%	Men (years)	40
Age		Household income	
25 or less	23.72%	Less than \$ 500,000 (US \$250)	27%
26-30	12.56%	\$500.001 (US \$250) - \$700.000 (US \$350)	15%
31-35	12.56%	\$700.001 (US \$350) - \$1.000.000 (US \$500)	13%
36-40	12.09%	\$1000.001 (US \$500) - \$1.500.000 (US \$750)	17%
41-45	9.77%	\$1.500.001 (US \$750) - \$2.000.000 (US \$1000)	6%
46-50	12.09%	\$2.000.001 (US \$1000) - \$2.500.000 (US \$1250)	7%
51-55	5.12%	\$2.500.001 (US \$1250) - \$3.000.000 (US \$1500)	7%

56 or more	12.09%	More than \$ 3,000,000 (US \$1500)	9%
Household structure		Household Size	
Infants: 0 - 2 years	4%	2 or less people	14.17%
Children: 3 - 12 years	16%	3-4	40.83%
Youth 13 - 17 years	15%	5-6	27.50%
Adults: 18 - 60 years	58%	7-9	11.67%
Seniors: 61 years or more	7%	10 or more people	5.83%
Occupation		Number of children	
Student	12.50%	0	53.75%
Employee	38.75%	1	19.17%
Independent	21.67%	2	15.00%
Housewife	21.25%	3	5.83%
Unemployed	4.58%	4	2.50%
Other	1.25%	5 or more	3.75%

Note: Sample size = 240 respondents.

3.3. Models Specifications

Discrete choice models are a particular class of econometric models that allows modelling choice among a set of finite alternatives. Using DCMs to assess the economic impacts of the deprivation experienced by disaster-impacted communities has certain advantages. First, it is an indirect method to assess the economic value of human suffering. Second, the methodology proposes scenarios that individuals may face in post-disaster environments (i.e. choosing among a set of alternatives to maximize their wellbeing subject to budget and other constraints).

The modeling effort involved testing multiple functional forms of the utility function, including linear, exponential, logarithmic, 2nd order Taylor Expansion, log-quadratic and Box-Cox transformations. For each model, the statistical significance of the parameters was tested and evaluated along with

their conceptual validity supported by the micro-economic theory. In this regard, the utility models described in the following sections have a suitable econometric foundation for the development of appropriate deprivation costs functions.

3.3.1. Functional Forms

In the designed scenarios, individual n is presented with two alternatives: (1) to purchase immediately (p) or (2) to wait (w) an additional time to receive drinking water for free, then $J = (p, w)$. The systematic utilities were specified using several functional forms as expressed in Models 1-3. Model 1 is a linear form, Model 2 is an exponential approximation, and Model 3 is a Box-Cox transformation.

Relevant attributes were included such as the unitary cost per liter of water (P), calculated as the quotient between purchasing price and the amount of liters of water; and the budget available for other consumption (AB), which was evaluated as the difference between the budget and the price of water. Note that the utility function of the purchase option is associated with the DT , while the wait option is related to the EDT .

Model 1: Linear

$$V_n(p) = ASC + \beta_{AB} AB_n + \beta_P P_n + \beta_{DT} DT_n \quad (18a)$$

$$V_n(w) = \beta_{DT} EDT_n \quad (18b)$$

Model 2: Exponential

$$V_n(p) = ASC + \beta_{AB} AB_n + \beta_P P_n + \beta_{DT} e^{(\beta_{DT1} \cdot DT_n)} \quad (19a)$$

$$V_n(w) = \beta_{DT} e^{(\beta_{DT1} \cdot EDT_n)} \quad (19b)$$

Model 3: Box-Cox

$$V_n(p) = ASC + \beta_{AB} AB_n + \beta_P P_n + \beta_{DT} (DT_n^\varphi - 1) / \varphi \quad (20a)$$

$$V_n(w) = \beta_{DT} (EDT_n^\varphi - 1) / \varphi \quad (20b)$$

According to the log-likelihood values at convergence, the Box-Cox model achieved a slightly better fit compared to the other models. Socioeconomic variables such as income level, household size, job, gender, presence of children in the household, and age were tested. However, none resulted statistically significant at the 5% level.

Notation:

$V_n(j)$: Systematic utility of alternative $j \in \{p, w\}$ associated to individual n .

ASC : Specific constant, defined for alternative p .

β_{AB} : Parameter associated with the available budget to purchase other supplies.

β_P : Parameter of water unitary price.

φ : Parameter of the Box-Cox function.

β_{DT} : Parameter related to deprivation time.

β_{DT1} : Parameter related to deprivation time, only for the exponential model

The error terms ε_{ntj} were assumed to be IID Gumbel. To account for the panel effect due to the correlation among responses, a random term, $\xi \sim Normal(0, \sigma_\xi^2)$ was included (Cantillo et al., 2007).

3.4. Results and Analysis

Maximum likelihood was used to estimate the unknown parameters of the proposed models, replicating the individual choices observed based on the utility functions proposed in Section 4.1. All models included a pseudo panel effect that was estimated using 1,000 draws for each random variable.

Table 4 shows the results including the significant parameters for each model (t-statistics in parenthesis). The variables Unitary Price (P) and Available Budget (AB) are in thousand COP, while Deprivation Time (DT and EDT) are in hours. For the case of the Box-Cox model, the deprivation time parameters were scaled and multiplied by 0.01. The three models selected are those that offer the best combination of conceptual validity, microeconomic robustness, and statistical significance.

The results are interesting in several ways. To start, the relevant explanatory variables are significant, with t-values that exceed the minimum threshold at the 5% level. In addition, their corresponding signs are consistent with microeconomic theory. The models confirm the convex nature of deprivation costs, although the behavior of the utility functions follow a linear tendency. The goodness of fit indicators (i.e. the adjusted rho squared and the log-likelihood at convergence) are similar for the three models. A relevant point is that choices of individuals who had been impacted by a disaster were statistically equal to those who had not been.

The estimated parameters show that the cost and time-related attributes represent a disutility to individuals. The negative sign of the time parameter indicates that a longer period of deprivation significantly reduces the utility of the individual and its welfare. Similarly, an increase in water price makes less accessible its consumption and limits the option of meeting other essential

needs such as medicine, transportation, and communications. In addition, a larger Budget increases the individual willingness to pay for water. This, combined with the fact that the income variable is not significant, indicates that the modeling effort successfully removed the income effect from the willingness to pay estimates. The absence of socio-economic characteristics from the list of significant variables in the models is consistent with the results found by Holguin-Veras et al. (2016).

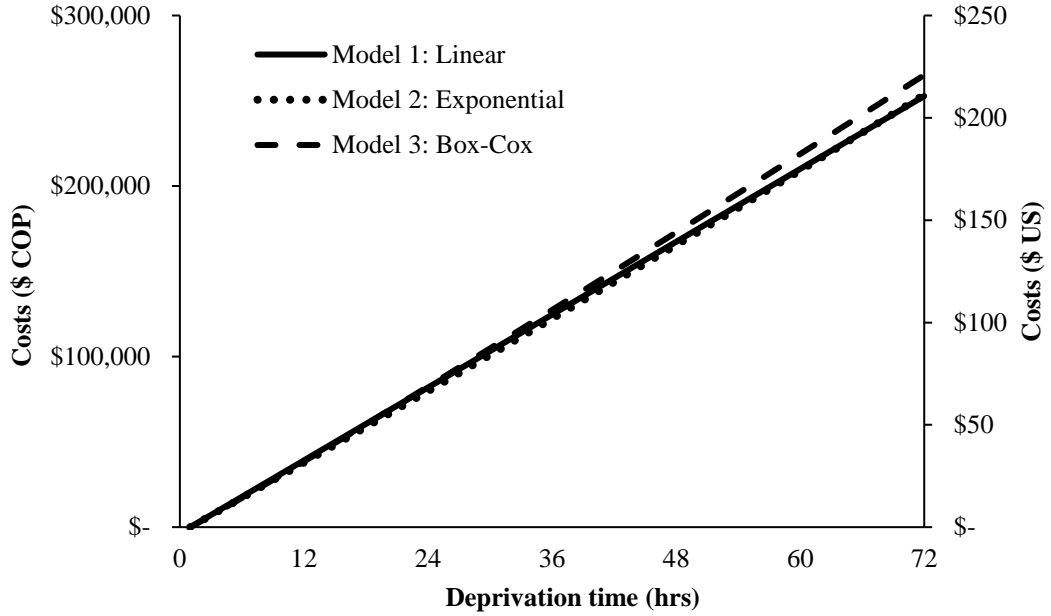
Regarding the Box – Cox model, the τ parameter is positive and slightly higher than one, which indicates that the DCFs have a monotonically increasing form with respect to the DT, which has been previously shown by Holguín-Veras et al. (2016). This behavior is also described by the parameter β_{DT} in Model 2. The larger the time without access to water, the higher the utility of the individual. The likelihood-ratio test indicates that Models 1 and 3 are equivalent (Ortúzar and Willumsen, 2011). This means that model specifications whose utility functions are linear-in-the-parameters provide a good representation of the individuals' behavior for the studied context.

Table 4: Econometric Models

Variables	Parameter (t-test)		
	Model 1 Linear	Model 2 Exponential	Model 3 ⁺ Box-Cox
Constant (ASC)	1.66 (4.84)	1.67 (5.06)	1.67 (4.95)
Available Budget AB (β_{AB})	1.59E-02 (9.06)	1.59E-02 (9.10)	1.59E-02 (8.85)
Unitary Price P (β_P)	-2.25E-01 (-10.15)	-2.25E-01 (-10.07)	-2.25E-01 (-10.48)
Deprivation Time DT, EDT (β_{DT})	-5.67E-02 (-4.76)	-44.10 (-6.32)	-5.95 (-2.53)
Box-Cox parameter (φ)	--	--	1.04 (4.43)
Exponential time (β_{DT1})	--	1.23E-03 (8.54)	--
Panel effect, Standard deviation (σ_{ε})	2.18 (13.87)	2.18 (14.64)	2.18 (14.56)
Number of Parameters	5	6	6
Observations	2400	2400	2400
Adjusted rho squared	0.395	0.396	0.397
Log-likelihood	-999.74	-999.76	-999.72

+ Time-related variables were scaled by 0.01 in Box Cox transformation,

The models allow estimating appropriate DCFs with micro-economic foundation measuring the change in consumer surplus as defined in Equation 10. Using sample enumeration and panel analysis techniques, an assessment of the changes in benefits was conducted and results are plot in Figure 7. In order to observe the behavior of the functions, the estimates were extrapolated up to a deprivation time of 120 hours (time at which an individual dies from water deprivation). All DCFs show a monotonically increasing behavior that is also convex with respect to deprivation time. The figure shows that up to 48 hours, the three models produces similar estimates. From this point in time, the Box-Cox model produces slightly higher estimates.



Note: US \$1 \approx COP 2,000 approximately

Figure 7: Costs for Water Deprivation

According to the Box-Cox model, the monetary value for 6 hours of water deprivation is about COP 20,528 (US \$10.20 at the time this study was conducted). Meanwhile, estimation of costs when such time is 72 hours are about COP 260,000 (US \$130). As a reference point, the market value for one liter of bottled water is approximately COP2,000 (US \$1). It is obvious that results are sensitive to the specification of the utility function.

Moreover, the results indicate that the deprivation time is a significant attribute that the individuals account at the time of making their choice. Table 5 shows the elasticities for each attribute in the model. The alternative *wait* is highly sensitive to deprivation time compared to *purchase* for this specific attribute.

Table 5: Direct Elasticities in the Choice Model

Attribute	Alternative	
	Purchase	Wait
Deprivation Time - DT	-0.14	-1.45
Unitary Price - P	-0.31	-
Available Budget - AB	0.13	

Figure 8 presents the elasticities of deprivation costs over time. It can be noticed that the elasticities are all greater than one, which denotes a high sensitivity with respect to deprivation time. The high values of elasticity are explained by the fact that water is an essential good.

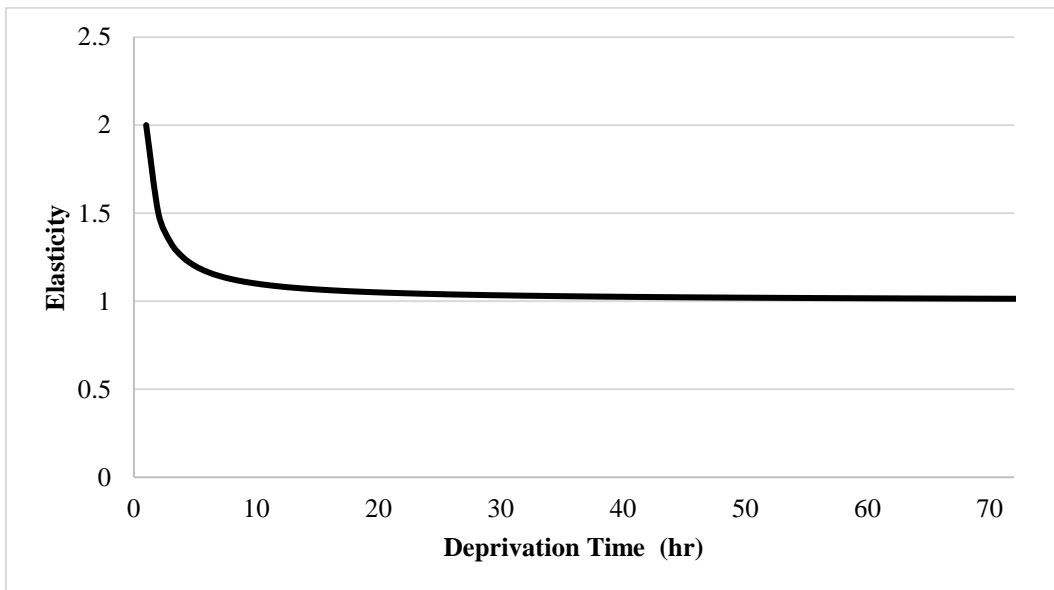


Figure 8: Deprivation Cost Elasticities

This valuation of cost due to changes in welfare can be integrated into PD-HL models to prioritize delivery operations. In this new scheme, the objective function would be able to value the economic impacts perceived by the affected community without the need of proxy measures that do not reflect the reality of disaster settings. It is clarified that the models estimated here are useful only in the regional context to which the sample belongs and for the commodity

used (i.e. drinking water). Transferability of results might be limited by the lack of similar studies. Though it could be analyzed within the context of other developing countries, or those with similar conditions to the case of Colombia.

The econometric estimation of changes in personal benefits due to deprivation time has important implications for HL modeling. The results clearly show that it is possible to estimate costs for timely provision of a critical supply that are consistent with real life.

3.5. Conclusions

This chapter a novel approach to assess the economic impacts of relief distribution of water to disaster-impacted communities is proposed. The methodology combines discrete choice modeling and stated preferences techniques to estimate the changes in the individuals' welfare. The monetary costs due to changes in personal benefits produced by the relief effort are measured as the change in consumer surplus as personal utility decreases when the deprivation time increases. Such consideration allows mathematical formulations with the inclusion of not only operational costs but also externalities related to disaster relief giving place to a more equitable distribution of scarce resources.

Three models were estimated following a linear, an exponential and Box-Cox transformations, including key variables such as deprivation time, budget and unitary cost of purchasing drinking water. The results show that economic valuation of water deprivation is larger than the market price. Therefore, the traditional models, which only consider private logistics costs are not appropriate in estimating the impacts on the population. The proposed models are characterized by strictly increasing and convex form functions with estimates that are highly sensitive to the specification of the utility function.

The main challenge posed by the estimated functions is their non-linearity when included into PD-HL models that, substantially increases the complexity of solution algorithms.

For deprivation times under four hours, the models estimate values comparable to the market price of water. Nevertheless, the costs quickly increase with the accrual of suffering due to the lack of access to water. After ten hours, the cost elasticity with respect to deprivation time becomes higher than one, reflecting its high level of sensibility.

Several limitations of the proposed approach are acknowledged. Firstly, the existence of serious philosophical objections to the valuation of human suffering. There are also questions about the ability of the instruments to provide reliable estimates, particularly in the case of individuals that have not previously experienced any disaster situation. In this context, the results show that WTP of individuals with and without previous experience in disasters were statistically similar. The experiment was rigorous and was supplemented with the “cheap talk” technique for bias minimization that is usually a limitation of stated preferences surveys. Attending these limitations, all possible measures should be taken to mitigate them. Even considering the previous concerns, the results from this study are a relevant contribution as the models can be incorporated into post-disaster humanitarian logistic models to avoid the use of proxy measures that do not properly account for human suffering. The inclusion of this component into the humanitarian models increase the complexity, though it enhances the realism of the setting represented while produces a fair distribution of scarce resources.

4 INFLUENCE OF INDIVIDUAL'S SOCIOECONOMIC CHARACTERISTICS AND RANDOM EFFECTS ON DEPRIVATION COST FUNCTIONS

4.1. Introduction

Natural disasters affect people differently and at a variety of scales, affecting the most vulnerable groups (i.e. the poor, infants, women and the elderly) the most. Disasters such as the South-East Asia earthquake and tsunami that occurred in 2004 and the 2010 earthquake in Haiti give a dimension of the effect on these different segments of the population. In the first disaster, more than 220.000 people lost their lives (Suppasri et al. 2012), being most of them women. In countries such as Sri Lanka and Indonesia, one-third of the casualties were children, and thousands of others were registered as orphans (Unicef 2009). The second disaster killed over 220.000 Haitians and caused the displacement of 2.3 million people (UNDP 2010). It is estimated that 1.5 million children were affected while another 38.000 died. There were 103.000 registered cases of infants unprotected by relatives or family (Unicef 2011). According to Unicef (2011) moments after the earthquake, just 5% of the poorest women in the country had access to medical supplies. These statistics illustrate how impact varies according to socio-economic characteristics. It implies that each group experiment diverse needs and assistance. In this sense, a proper and efficient humanitarian assistance process should respond in a differentiated way considering the specific requirements of each group, especially the most vulnerable, as social inequities exacerbate suffering. Given

these remarkable dissimilarities between social groups and their suffering, it is mandatory for humanitarian logistic models to respond to the different needs of each socio-economic group. In this sense, the humanitarian delivery process will be more equitable bringing proper assistance to the affected population.

One way to deal with this matter is using Deprivation Cost Functions (DCFs) for each socio-economic group. However, the current econometric approaches (including the models presented in chapter 3) did not include socioeconomic variables on individuals. This entails considering affected people as a homogeneous population. Consequently, the deprivation costs are expressed only in terms of deprivation time without any consideration of the socioeconomic or demographic aspects of the affected people, which limit their use. It evokes the debate about equity measurement in humanitarian logistics involving social costs. (Holguín-Veras et al. (2016), Cantillo et al. (2017a). To fill this gap, in this chapter advanced discrete choice models based on the random utility theory are used to adjust DCFs that consider systematic and random heterogeneity over individual preferences and responses. To accomplish this objective, a new stated choice survey was designed and applied to people living in areas affected by floods and earthquakes in Colombia. As a result, two different kinds of family models were specified with socio-economic variables and random variations in order to include specific measures equity over the population.

This chapter is organized as follows: Section 4.2 describes the data collection process, making special emphasis on the experimental design used in this article as well as on the descriptive analysis of the sample. Section 4.3 presents the models specifications considering systematic and random variation. Section 4.4 discusses the results of the proposed models and the influence of heterogeneity in the DC. Finally, Section 4.5 states general conclusions.

4.2. Experimental Setup II: Providing a Basic Food Kit as a Scarce Supply

The data used in this chapter to estimate the models were collected from a stated preference (SP) survey that was applied to independent people and heads of families from different areas of Colombia that have been affected by natural disasters. The surveys were conducted from September 2014 to November of the same year. In most cases, the respondents were habitants of small towns affected by the winter emergency that occurred in Colombia during 2010 (Sahagún, Caimito, Suan, Candelaria, Santa Lucía and Campo de la Cruz) (Hoyos et al. 2013) and by the Armenia-Colombia earthquake occurred in 1999. Data also included people from the two largest capitals of the Colombian North Coast (Barranquilla and Cartagena). The breakdown of the sample by location was: Armenia (29%), Barranquilla (11%), Cartagena (10%), Sahagún (11%), Caimito (11%), Suan (8%), Candelaria (6%), Santa Lucía (7%) and Campo de la Cruz (7%). Figure 9 presents the Colombian map, pointing out the cities where the SP survey was applied. It also shows the areas affected by the floods during 2010 and the earthquake during 1999.

The survey gathered data from (1) socioeconomic information at household and individual level (e.g. age, gender, household size, family income level, occupation, educational levels) (see Appendix 1 for the survey applied); (2) the respondents' choice preferences according to the SC experiment next presented, which allowed the generation of a hypothetical market (see Appendix 2 for an example of the stated preference survey cards used). As the SC experiment was based in a natural disaster context, it was hypothesized that individuals who have experienced the devastation of natural disasters, or who have seen first-hand their devastating impact, would be able to provide better SP data than those who did not have such experience.

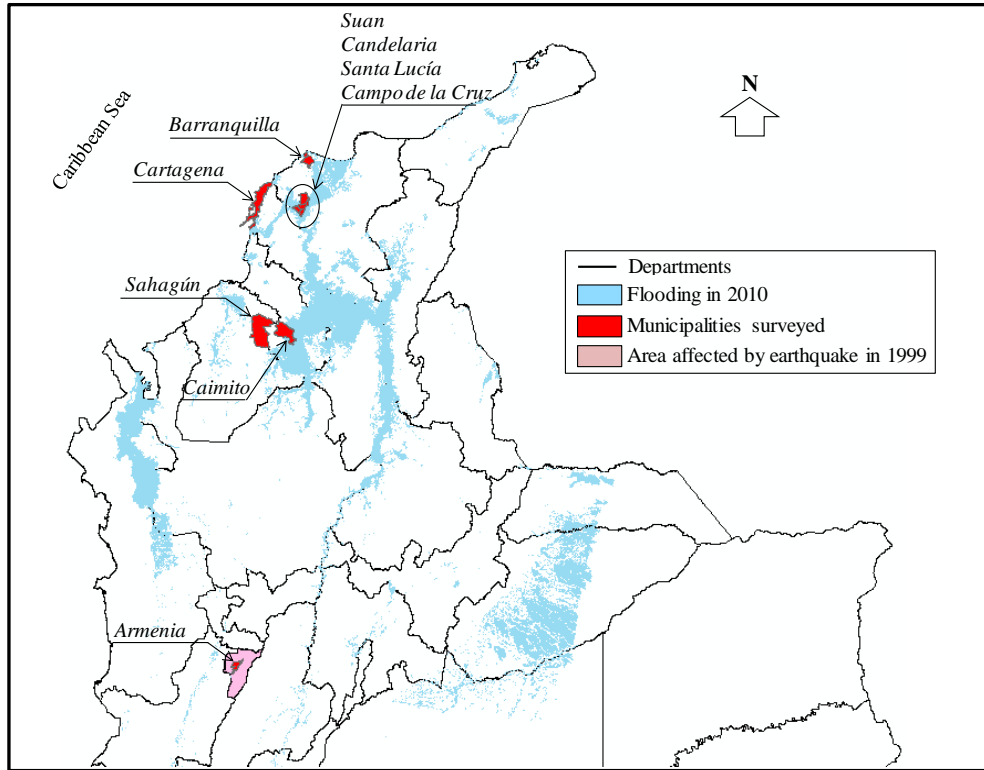


Figure 9. Study Area in Colombian

As it is known, a set of critical supplies is required by affected people after a disaster occurrence (e.g. water, fuel, medicines, food, first-aid kit, personal hygiene kit, and clothing, among others). However, for the purpose of this chapter and its analyses, a basic food kit (including water) was considered since it is a common supply in the international humanitarian logistics processes. Moreover, all affected people need access to this kind of supplies to stay alive. If the affected people are deprived of water and food for an extended period, they can suffer permanent damage and even die (Holguín-Veras et al. 2016). Additionally, previous disaster experiences show that water and food are essential supplies in the initial days of a response. In this sense, the SC experiment presented to respondents allowed us to collect their preferences about nine hypothetical choice scenarios of being a disaster survivor, where

they had two options to handle the local scarcity of critical supplies: to purchase (p) a basic food kit to cover their immediate needs, considering their budget restriction, or to wait (w) longer for free humanitarian aid to arrive, which means deferring consumption. The following hypothetical situation was presented to respondents:

“Let’s suppose that a disaster has occurred in the municipality where you live. Your house has been destroyed, the supermarkets, stores and any other place where you could buy supplies have also been destroyed, and there is a severe food shortage. Your family survived the natural disaster, and they have spent several hours without eating or drinking since the event occurred; however, you have a certain amount of money available in your pocket.

We are going to show you nine choice scenarios. In each case, you will choose between purchasing a basket of basic supplies with enough food to feed a person for one day, or to wait longer until the humanitarian aid arrives with the same supplies for free. If you choose the second option, you will be able to keep the money for other needs.”

The description of the choice context was accompanied by pictures extracted from the disasters that had occurred previously in the area to achieve a better understanding of the proposed scenario, as recommended by Carson et al. (1994). According to the hypothetical situation presented, five attributes were considered according to the survey described in chapter 3. (i) the current deprivation time (DT), which is the time without eating since the time the event occurred; (ii) waiting time (WT), which is the additional deprivation time waiting to receive a free humanitarian aid (a free food kit); (iii) the total budget

to purchase (B); (iv) the price of one food kit (P); and (v) the available budget to purchase other supplies ($AB = B - P$).

As food and water are not the only necessity after the occurrence of a natural disaster, affected people try to maximize their wellbeing subject to their budget restrictions. If the respondents choose to purchase the basic food kit to cover their needs for water and food, given a certain DT , then their AB would be reduced, and that could impede the meet other essential needs (e.g. medicine, transportation, communications). Thus, it is very important conserving money for other supplies. However, if the respondents want to keep their AB and cover their needs for food and water later on, then an additional WT is required until the humanitarian assistance arrives and distributes the free food and water. In this context, the purchasing option (p) is related to the DT , while the waiting option (w) is related to an expected deprivation time (EDT) until the arrival of the humanitarian assistance ($EDT = DT + WT$). As used in the first survey, the budget was considered an experimental variable in order to remove the income effect from the responses. Individuals must respond based on the given scenarios and not on their socio-economic condition. All mentioned attributes were specified with four variation levels as presented in Table 6.

Table 6. Attributes of experimental design

Attributes	Levels	Values
DT : Deprivation time (hours)	4	4, 8, 12, 16
WT : Waiting time (hours)	4	4, 8, 12, 16
P : Total price of supplies. COP*/ basic food kit (US \$)	4	10,000 (5), 20,000 (10), 30,000 (15), 40,000 (20)
AB : Available budget. COP (US \$)	4	0 (0), 10,000 (5), 20,000 (10), 30,000 (15)

*When the survey was applied 1USD \approx 2000 COP

These attributes and their values were collected through focus groups developed with people that have been affected by natural disaster. These people were asked about their experience during the humanitarian assistance process. They were also questioned about aspects related to good and services highly demanded, average assistance time and levels of confidence in local emergency agencies. With the information collected from the focus groups, a pilot SP survey was created and applied. As a result, very high values of *DT* in the pilot survey were found unrealistic for the respondents. In consequence, both *DT* and *WT* were adjusted from 4 to 16 hours in the SC experiment since the longer the *DT*, the more difficult it becomes for the respondents to imagine the realities of the scenarios, and the less reliable their responses become. The ranges of values used for the other attributes were: *P* from COP \$10,000 to COP \$40,000 and *AB* from COP \$0 to COP \$30,000. The price provided by the respondents, originally in Colombian Pesos (COP), were converted to US dollars (\$) using an exchange rate of COP 2,000 per US \$1 (Banco de la República 2015). As a reference point, the market value of the basic foods kit is around COP \$10,000 (US \$ 5).

As the main effects of four attributes, each with four levels of variation, would require a large number of choice scenarios (36) following an orthogonal factorial design (Hicks 1973), a fractional factorial design was used, which is more feasible to respondents since they can face fewer choice situations with more attention (Ortúzar 2011). In consequence, the orthogonal design was divided into four blocks by using the software Ngene® (ChoiceMetrics 2012); then, each respondent faced nine choice situations. Every respondent was randomly assigned to one of these blocks. Additionally, the order of presentation of the scenarios was also randomized to avoid order bias. The

design ensures attribute level balance within each of the blocks (Louviere et al. 2000). The Appendix 1 presents the final SC survey.

The SP survey was applied to 560 respondents randomly selected. Data includes people previously impacted by a disaster (64%) and not impacted (36%). The Colombian Office of Prevention and Disaster Response (in Spanish “*Oficina de Prevención y Atención de Desastres*”) provided the database for the first group. Interviews were performed face-to-face. The data collected were post-processed, coded in an electronic data set, cleaned, and reviewed to ensure they represented the respondents’ answers. After depuration and exclusion of lexicographic individuals, 487 surveys were used for modeling purposes.

The interviewees represented a broad range of socio-economic conditions. They were people aged between 18 and 86 years, of whom 46% were men and 54% women. The average sample age was 47 years, and the average size of a family was four persons. The proportion of respondents with children aged 10 years or less was 47%, and with adolescents (from 11 to 18 years old) was 44%. Regarding employment, 37.1% of the individuals were employees in formal businesses; 21.1% of the sample were independent workers, mostly in the informal sectors of the economy; 30.5% stayed at home; 4.5% were unemployed, and 1.6% were students. The distribution by income was as follows: low-income (levels 1 and 2): 71.6%; medium-income (levels 3 and 4): 25.2, and high-income (levels 5 and 6): 3.8%. Collecting data from a heterogeneous population improves the models quality due to the independent variables are likely to cover the entire range of values. This is why such variety of cities and towns and population groups with and without previous disaster experience were included. A more detailed description of socioeconomic characteristics of the sample is presented in Table 7.

The collected information is consistent with some demographic characteristics of the Colombian population at the time of the survey. The average household size (4.0) is comparable to the general population (3.9 individuals per household). The distribution of households by income is also similar to the general population in the country (DANE 2014), which indicate that the data provide a consistent representation of the population.

Table 7. Socioeconomic characteristics of the sample

Gender		Average age by gender	
Male	46%	Women (years)	46
Female	54%	Men (years)	48
Age		Household income level	
25 or less	5.0%	1 (poorest)	41.3%
26-35	17.7%	2	30.4%
36-45	23.2%	3	20.7%
46-55	25.0%	4	4.5%
56-65	19.1%	5	2.11%
66 or more	10.0%	6 (richest)	1.1%
Number of children and adolescents		Occupation	
0 children: 0 - 10 years	53%	Student	1.6%
1 or 2 children: 0 - 10 years	39%	Employee	37.1%
3 or more children: 0 - 10 years	8%	Independent	21.1%
0 Youth: 11 - 17 years	56%	Housewife	30.5%
1 or 2 Youth: 11 - 17 years	38%	Unemployed	4.5%
3 or more Youth: 11 - 17 years	6%	Other	5.2%
Household Size		Educational levels	
2 or less people	13.9%	Elementary school	22.9%
3-4	44.5%	High school diploma	30.9%
5-6	28.9%	Non-degree programs	10.7%
7-9	11.1%	College degree	30.0%
10 or more people	1.6%	None	6.6%

Note: Sample size = 560 respondents

About the hypothetical choice scenarios presented to respondents, 45% of male and 55% of female chose the purchase option whereas 48% of men and 52% of women were willing to wait for free humanitarian aid. The former proportions show a notable balance between the individual's preferences.

Data obtained from the SC experiment was used for estimating ML models using the simulated maximum likelihood method. The modeling effort is reported in the next section.

4.3. Models Specifications with Systematic and Random Variation

In order to analyze the influence of systematic and random variations among individuals as well as its effects into the estimation of proper DCFs, several ML models were specified. This econometric approach allows modeling choice among a set of finite alternatives, such as was presented to respondent in the SC experiment. Additionally, ML models allow handling, in a relatively simple way, many sources of individual variability (Ortúzar 2011), making it the most suitable model for the purpose of this chapter.

Two families of ML models aiming to consider the nonlinear behavior of DCFs are presented. The first family ($ML_1 - ML_2$) is specified with Box-Cox transformations of the time-related attribute, while the second family ($ML_3 - ML_4$), with exponential transformation. Each family includes a basic model, which only considers the variables of the experiment and panel effect (models ML_1 and ML_3) to correlate observations from the same individual. On the other hand, models ML_2 and ML_4 consider systematic and random heterogeneity over individual preferences and responses. The systematic heterogeneity was captured by the interaction between deprivation time, regional categories (where different kind of disasters have occurred) and individuals'

socioeconomic characteristics, while the random heterogeneity was captured assuming that the time parameter varies with a normal probability distribution among individuals.

Taking into account the places where the data were collected, three regional categories were considered: people living in places with low risk (C_1), people living in places at risk of flooding (C_2) and people living in places at risk of earthquake (C_3). The first group includes Barranquilla and Cartagena. The second group is composed of the six small towns affected by the winter emergency occurred in Colombia during 2010 (see section 3). The third group is the city of Armenia, which suffered a destructive earthquake in 1999. These regional categories allow us to analyze the disaster impact on people, the regional influence and verify heteroscedasticity.

According to the choice alternatives presented to the respondent in the SC experiment, the utility function of the purchase option (p) was specified considering DT , whereas the utility function of the waiting option (w) involves $EDT = DT + WT$. The utility of option p also includes the unit price of a basic food kit (P) and the available budget (AB). On the other hand, socioeconomic variables such as gender (G), age (E) and the high presence of children at home (PCH) as well as dummy variables for the regional categories (C_i) were included in interaction with time in models ML_2 and ML_4 . Table 8 presents a more detailed description of the attributes used for the specifications of the utility functions.

Table 8. Attributes used in the specification of utility functions.

Notation	Variable	Description
P	Unit price of a basic food kit (Thousands COP)	
AB	Available budget (Thousands COP)	
G	Binary variable associated with the individual's gender	1: If the individual is a woman 0: Otherwise
A	Binary variable associated with the individual's age	1: If the individual is older than 50 0: Otherwise
PCH	Binary variable associated with the high presence of children at home	1: If percentage of children at home is greater than 30% 0: Otherwise
DT	Deprivation time (hours)	
WT	Additional waiting time for free supply (hours)	
C_i	Binary variable associated with the regional category i .	1: If the individual belongs to regional category i ; 0: Otherwise C_1 Living in low risk places (reference category) C_2 Living in places at risk of flooding C_3 Living in places at risk of an earthquake.

As presented in Table 9, the models ML1(Eq. 15) and ML3 (Eq. 17) consider a homogeneous population given that these do not take into account any socioeconomic variables while the models ML2 (Eq. 16) and ML4 (Eq. 18) consider a heterogeneous population as explained above, making possible to study and compare the effect of heterogeneity on DC.

Notation used in Table 9:

$V_n(j)$: Systematic utility of alternative $j \in \{p, w\}$ associated to individual n .

ASC : Specific constant, defined for alternative p .

β_{AB} : Parameter associated to AB .

β_P : Parameter associated to the unit price P of a basic food kit.

β_{DT}, β_{DT1} : Parameter associated to deprivation time.

δ_{GT} : Parameter associated to the interaction between the individual's gender and deprivation time.

δ_{AT} : Parameter associated to the interaction between the individual's age and deprivation time.

δ_{PCHT} : Parameter associated to the interaction between the high presence of children at home and deprivation time.

δ_{C2T} : Parameter associated to the interaction between the regional category 2 (C_2) and deprivation time.

δ_{C3T} : Parameter associated to the interaction between the regional category 3 (C_3) and deprivation time.

The distribution of the random parameter of time in the ML models was assumed to be $\beta_T \sim Normal(\beta_T, \sigma_{\beta_T}^2)$, whereas ε has a Gumbel IID distribution. The additional error component $\xi \sim Normal(0, \sigma_{\xi}^2)$ was added to consider the panel effect in all alternatives. All models were estimated using simulated maximum likelihood.

Finally, for each model presented, the statistical significance of the parameters was tested and evaluated along with their conceptual validity supported by the microeconomic theory. In this regard, the utility models described in the following sections have a suitable econometric foundation for the development of appropriate deprivation costs functions.

Table 9. Models Specifications

1 st family of ML models.	
ML_1	
$V_n(p) = ASC + \beta_P \cdot P_n + \beta_{AB} \cdot AB_n + \beta_{DT} \cdot DT_n^{(\varphi)} + \xi_n$ $V_n(w) = \beta_{DT} \cdot (DT_n + WT_n)^{(\varphi)}$	(21)
$ML_2.$	
$V_n(p) = ASC + \beta_P \cdot P_n + \beta_{AB} \cdot AB_n + (\beta_{DT} + \delta_{GT}G_n + \delta_{AT}A_n + \delta_{PCHT}PCH_n + \delta_{C2}C2_n + \delta_{C3}C3_n + \eta_{Tn}) \cdot DT_n^{(\varphi)} + \xi_n$ $V_n(w) = (\beta_{DT} + \delta_{GT}G_n + \delta_{AT}A_n + \delta_{PCHT}PCH_n + \delta_{C2}C2_n + \delta_{C3}C3_n + \eta_{Tn}) \cdot (DT_n + WT_n)^{(\varphi)}$	(22)
2 nd family of ML models.	
ML_3	
$V_n(p) = ASC + \beta_P \cdot P_n + \beta_{AB} \cdot AB_n + \beta_{DT} \cdot e^{\beta_{DT1} \cdot DT_n} + \xi_n$ $V_n(w) = \beta_{DT} \cdot e^{\beta_{DT1} \cdot (DT_n + WT_n)}$	(23)
$ML_4.$	
$V_n(p) = ASC + \beta_P \cdot P_n + \beta_{AB} \cdot AB_n + (\beta_{DT} + \delta_{GT}G_n + \delta_{AT}A_n + \delta_{PCHT}PCH_n + \delta_{C2}C2_n + \delta_{C3}C3_n + \eta_{Tn}) \cdot e^{(\beta_{DT1} \cdot DT_n)} + \xi_n$ $V_n(w) = (\beta_{DT} + \delta_{GT}G_n + \delta_{AT}A_n + \delta_{PCHT}PCH_n + \delta_{C2}C2_n + \delta_{C3}C3_n + \eta_{Tn}) \cdot e^{\beta_{DT1} \cdot (DT_n + WT_n)}$	(24)

4.4. Results and Analysis

For all models, the estimated coefficients, t-tests (in parenthesis) and other relevant goodness-of-fit statistics are shown in Table 10. The estimation process was based on 4,383 observations obtained from 487 individuals. According to the values of the log-likelihood at convergence and the adjusted rho-squared index (Ortúzar 2011), models with systematic and random heterogeneity (ML2, ML4) provide a better fit to the data than models that do not consider variations in tastes (ML1 and ML2). In addition, the estimated coefficients of attributes included in the experiment for all models display statistical significance at least at 95% confidence, and their signs are conceptually consistent with microeconomic theory. The results indicated that all attributes included in the experiment are relevant for individuals when making their choice. The standard deviations of the deprivation time parameter are highly significant in models ML2 and ML4, which denote the presence of random heterogeneities in tastes, in addition to the systematic ones.

When both families of models are contrasted, the goodness of fit indexes are similar for comparable models (ML1 vs ML3 and ML2 vs ML4). However, the functional form of the exponential model increases its convexity faster than the Box-Cox. The behavior of the exponential transformation is more consistent with the expected variations in a DCF.

The negative signs associated with the parameters of time and price evidence *-ceteris paribus-* that an increase in any of these variables would represent a decrease in the individual's utility. An increase in the deprivation time of food and water in a disaster context would reduce their well-being. About the first family of ML models (Box-Cox), the τ coefficients are positive and close to the quadratic approximation, which offers microeconomic evidence of the nonlinear relationship between DC and DT (something not observed in chapter 2). In the same sense, the second family of ML models (Exponential) displays a positive sign in the exponential time parameter (β_{DT1}), which also supports the strictly increasing and convex relation between DC and DT, a previously mentioned characteristic of the DCFs.

Statistical significances of most parameters associated with the proposed interactions in models ML2 and ML4 indicate that different socioeconomic segments assign different values

to DT. It would show that there is heterogeneity in preferences among individuals. As can be seen in Table 10, parameters associated with the interaction between the individual's gender and DT (δ_{GT}) are non-significant at 90%, but their negative sign suggest that the marginal impact of deprivation time is slightly greater for women than for men. On the other hand, the interactions between the individual's age and DT (δ_{AT}) are significant at 95% level and also has a negative sign, suggesting that the elderly (those over 50 years of age) are more sensitive to deprivation time than the young. In the same way, a high presence of children at home induce people to have a greater incentive to prevent prolonged periods of deprivation as it implies a greater moral obligation.

The previous results are in accordance with the Pan-American Health Organization -PAHO (2012b), which indicates that natural disasters affect people who have different social characteristics in different ways. Moreover, differences in cultural and physical conditions can become more evident after a natural disaster (PAHO 2012b). Additionally, studies developed by different researchers have reported that females have a greater perception of risk than males (Noland 1995b);(Iragüen and Ortúzar 2004); (Cantillo et al. 2015), which might be a rational justification for the slightly higher valuation that women assign to DT.

This disaggregated valuation considering socioeconomic characteristics is useful in terms of introducing enhancements to the mechanisms employed to distribute humanitarian aid. In consequence, the models would adjust to the needs of the most vulnerable population affected by disasters. Similarly, the estimated coefficients of the regional categories tested show valuable information. Interestingly, according to Models ML2 and ML4, there are not significant differences between regional categories C1 and C3. This result may be related to socioeconomic characteristics. Both categories represent urban environments, as Barranquilla, Cartagena and Armenia are capital cities. In contrast, for category C2, the interaction was positive and significant at 90%, suggesting a lower sensitivity to deprivation time. The latter are rural towns whose income level is substantially lower than that of capitals'. This may explain why the willingness to pay is lower in the poor sectors affected by floods.

Table 10. Modeling results

<i>Parameter (Notation)</i>	Mean (t-test)			
	ML1	ML2	ML3	ML4
	Box-Cox	Box-Cox	Exponential	Exponential
<i>Constant (ASC)</i>	-2.49 (-15.27)	-2.63 (-17.04)	-2.52 (-15.55)	-2.65 (-17.95)
<i>Available budget (β_{AB}) (thousands COP)</i>	0.0547 (14.08)	0.0624 (15.21)	0.0525 (13.67)	0.0602 (15.00)
<i>Price (β_P) (thousands COP)</i>	-0.0179 (-4.86)	-0.0217 (-5.72)	-0.0160 (-4.34)	-0.0196 (-5.23)
<i>Deprivation Time (β_{DT}) (hr)</i>	-0.0264 (-4.46)	-0.0235 (-4.40)	-2.08 (-5.67)	-1.63 (-4.83)
<i>Box-Cox Parameter (φ)</i>	1.83 (25.57)	1.91 (26.21)		
<i>Exponential time (β_{DT1})</i>			0.0524 (12.47)	0.0619 (11.64)
<i>Age-Time (δ_{AT})</i>		-0.00277 (-1.95)		-0.193 (-2.01)
<i>Gender-Time (δ_{GT})</i>		-0.00179 (-1.38)		-0.122 (-1.40)
<i>PCH-Time (δ_{PCHT})</i>		-0.00381 (-2.25)		-0.265 (-2.29)
<i>Floods regional Category 2 -Time (δ_{C2T})</i>		0.00280 (1.66)		0.199 (1.72)
<i>Earthquake regional Category 3-Time (δ_{C3T})</i>		-0.000441 (-0.25)		-0.270 (-0.22)
<i>Standard deviation of deprivation time (σ_η)</i>		0.0108 (4.77)		0.756 (5.46)
<i>Standard deviation, pannel effect (σ_ξ)</i>	1.20 (17.08)		1.19 (17.03)	
<i>Report of the estimation process</i>				
<i>Number of observations</i>	4383	4383	4383	4383
<i>Number of respondents</i>	487	487	487	487
<i>Measurement of adjustment</i>				
<i>Final Log-likelihood</i>	-2224.4	-2193.46	-2232.4	-2196.4
<i>Adjusted rho squared</i>	0.268	0.278	0.265	0.277

The estimated models allow adjusting appropriate DCFs that show a monotonically increasing, nonlinear and convex relationship on the DT, such as is proposed by Holguín-Veras et al. (2013). Figures 10 and 11 present the DCFs that result from applying the estimated coefficients for each model with the logsum formula (Equation 10). The results were extrapolated up to 72 hours. The simulations were carried out using sample enumeration methods.

In order to facilitate their practical application, given the complexity of the logsum, the resulting curves were fitted using polynomial regression models. As the second family of ML models is more convex than the first family, it was necessary to use a third degree Taylor

polynomial for the second family while a quadratic polynomial was used for the first family. The Adjusted R Square values of 0.99 in all cases show excellent fits for the curves, which can be used in humanitarian logistics models.

Although models ML2 and ML4 make it possible to estimate DCF for different groups, generic DCFs that only depend on DT are presented, and which are the average valuation of the sample. It is relevant to consider that typically, in the immediate aftermath of a disaster, relief groups will not have accurate data about the socio-economic characteristics of the people in need. In such cases, assuming that the individuals are observationally identical may be the best option (Holguín-Veras et al., 2013).

The monetary measures tend to be higher for ML models with systematic and random heterogeneity (ML2 and ML4). After 72 hours of waiting, the ML2 is 20% higher than ML1 while the ML4 is 21% greater than ML3. These results indicate that the use of restrictive specifications that impose homogenous behavior on the population would underestimate welfare loss measures. However, time-based studies in other contexts suggest that this result is not general and depends on the data nature, the model specification, and the context of choice used. These DCFs exposes the social costs of deprivation, which can be incorporated into comprehensive humanitarian logistics models to perform a risk analysis to evaluate humanitarian aid operations economically.

Estimates of deprivation costs deserve special discussion. Taking the market value of the basic kit to be around 10,000 COP (5 USD) as a reference, this value is obtained at 3 hours of deprivation according to the ML4 model. After 24 hours, the cost of deprivation exceeds 300,000 COP (150 USD) and grows rapidly to 7,500,000 COP (3,500 USD) at 72 hours. These estimates evidence the high weight of deprivation costs on social costs, far exceeding private logistical costs.

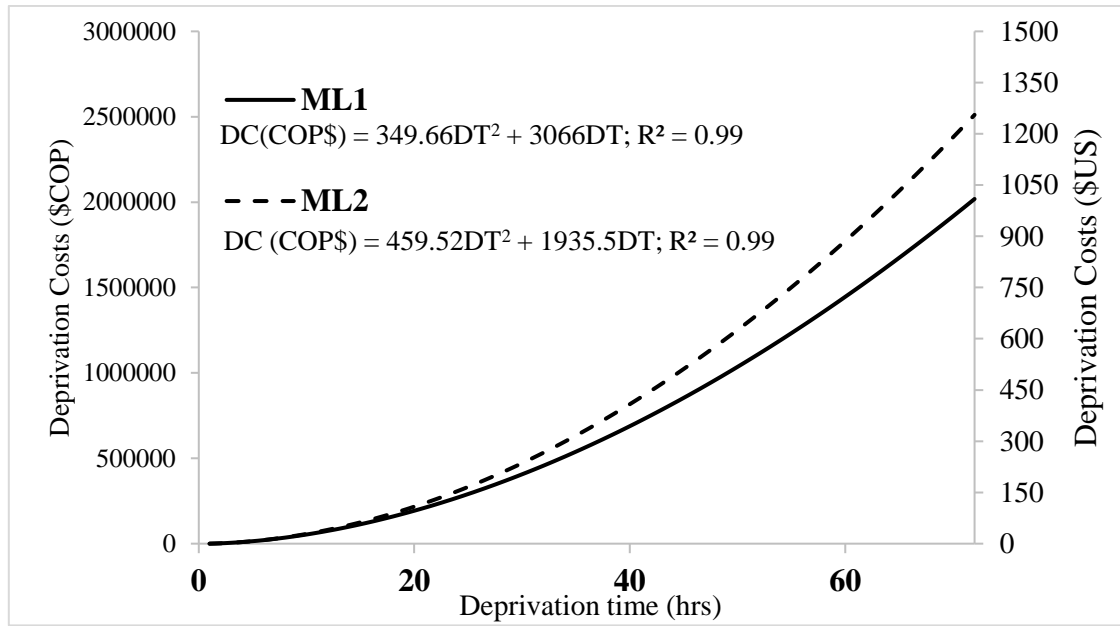


Figure 10. DCF for the first family of ML models

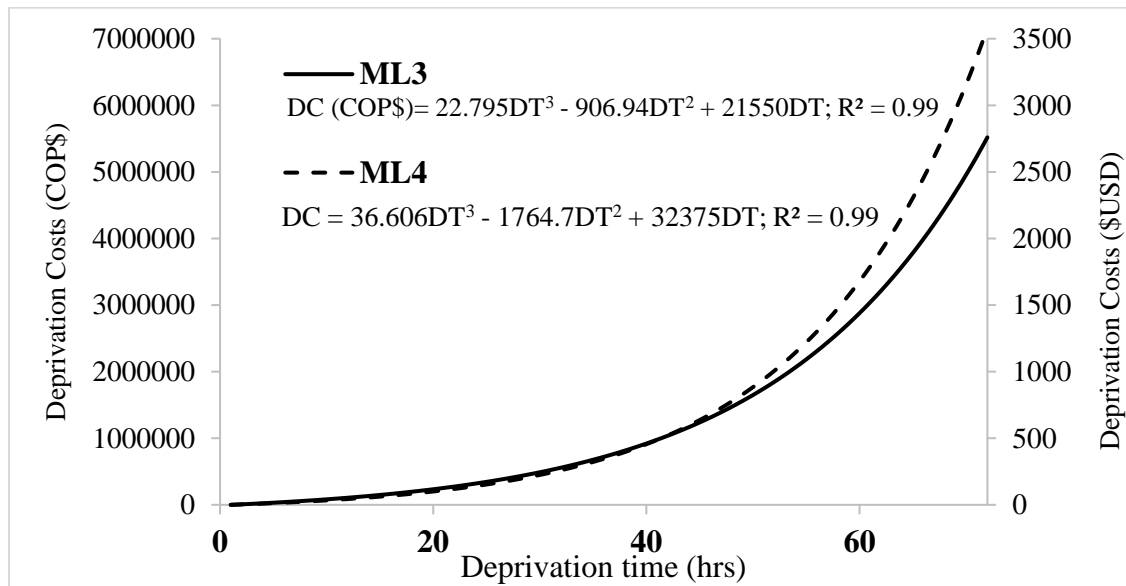


Figure 11. DCF for the second family of ML models.

Figure 12 shows the deprivation time elasticities for ML2 and ML4 models. All values are in the elastic range, which is an econometric evidence of the high sensitivity that exists between the DC and DT. For the Box-Cox model, elasticities have an asymptotic tendency. In the case of the exponential model, after 8 hours of deprivation time, elasticities increase monotonically.

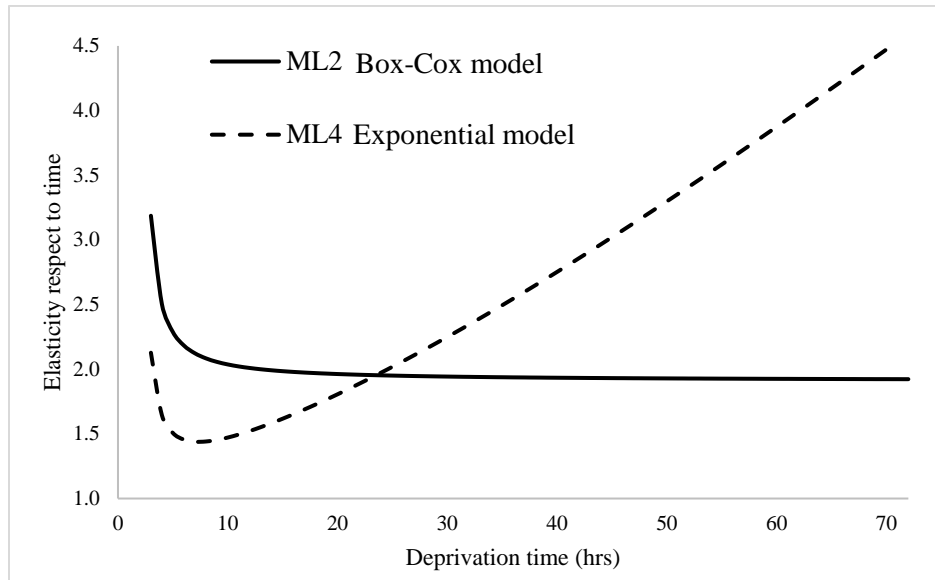


Figure 12. Deprivation time elasticity of DCFs

An aspect that deserves discussion is the transferability of the results to conditions other than those captured in the estimation data. Clearly, to reach definite conclusions about transferability, more extensive comparative studies are required to collect similar data in different socio-economic environments and places.

4.5. Conclusions

Estimated econometric models demonstrate that the externality derived from delays in the delivery of basic supplies display a strictly increasing and convex relation on deprivation time. The exponential function model calculated made a more realistic estimation for the first hours of deprivation possible. The inclusion of socioeconomic variables in the models, such as age and sex, revealed different valuations for the same attributes. This explains part of the heterogeneities between the preferences of individuals. The high monetary value of DC indicates that they have to be considered during the planning of humanitarian programs in order to move towards the social optimum. Presented results endorse the use of stated choice techniques for the valuation of externalities in disaster context using discrete choice techniques.

Different specifications of utility functions were compared with the purpose of validating the hypothesis about the existence of variations in population preferences. Statistically, significant differences were found in the assessment of deprivation time in socioeconomic

variables such as age, gender, and the proportion of children in the household. Results with ML models with random parameters allow us to conclude that there are other sources of heterogeneity which have a random nature related to the valuation of deprivation time. Specifications with systematic and random variations turned out to be suitable for the comprehensive modeling of the individuals' behavior.

The estimated models do not consider attributes related to the level of income and economic status. This is given that any attribute related to wealth was not part of the experiment or modeling. Nevertheless, it is expected that wealthy people have higher willingness to pay, a condition that can generate inequity in social assessment. In order to get equity, it is recommend considering a unique deprivation cost function for all individuals within the community affected by a particular disaster. However, if reliable information is available on the affected groups, it is possible to estimate differentiated DCFs, especially if policies have been drawn up to prioritize more vulnerable groups.

Determinants aspects of the ability to pay (e.g. household income, characteristics of the house, the level of preparedness) were not considered. In sum, the impact was evaluated according to determinants of deprivations costs and not from the ability to pay. In the experimental design, the amount of available budget was controlled to isolate the effect that the person's wealth could have produced in peoples' choice. The hypothetical scenario presented that the only available money is the one specified as budget. It allows separating the ability to pay for deprivation costs.

Results presented to validate the use of SC techniques for externalities valuation in disaster scenarios, making use of discrete choice techniques. In the same way, results show that DCFs are very sensitive to the specification of the utility function. It is due to the high monetary difference in DC between Box-Cox and the exponential function. The biases that can be produced both, by the poor specification of explanatory models and by the use of erroneous methodologies in the calculation of welfare, can be highly detrimental to the proper social evaluation of projects.

5 INFLUENCE OF ATTITUDES AND PERCEPTIONS ON DEPRIVATION COST FUNCTIONS

5.1. Introduction

As indicated in Chapter 1, social costs include the logistics cost associated with the relief distribution and the impacts of the relief effort on the affected people. The latter are measured in this work using DCFs that depends on the time the individual has no access to a good or service (according to models in chapter 3) and the socio-economic characteristics of the individual (as models developed in chapter 4). However, the role of psychosocial factors of people is an issue that have not been considered yet, which is fundamental to understand how individuals' attitudes and perception influence their behavior at the time to make a decision in order to achieve a better level of welfare in a disaster context.

Although human suffering produced by deprivation could be expected to be the same for all individuals with similar physiological conditions, local socioeconomic conditions and previous disaster experiences may influence its economic valuation. In this sense, in this chapter more accurate and predictive DCFs are estimated, including the influence of people attitudes and perceptions on the disaster preparedness as well as the relationship between these latent factors and the socioeconomic characteristics of individuals. To do that, two Hybrid Latent Variable - Discrete Choice Models (HLVDCMs) with different functional forms are estimated using the data collected and presented in chapter 4.

The organization of the chapter is as follows. The next section presents an overview about DCFs previously estimated and a theoretical framework of HLVDCMs. Section 5.2 presents a description of the attitudinal and behavioral indicator variables studied. Section 5.3 presents the model's specification. Section 5.4 gives the estimation results and its analysis. Finally, section 5.5 presents relevant conclusions.

5.2. Data for Latent Variables

The methodological approach used to estimate DCFs including LVs involves surveys designing and implementing as presented in section 3.2 and 4.2 as well as data for attitudinal and behavioral indicator variables. In this section this latter is presented and explained.

According to Walker (2001), perceptions are the individuals' beliefs or estimations of the attributes levels of a specific alternative of choice. Attitudes, in turn, reflect individuals' needs, values, tastes, and capabilities that can explain part of the random term included in the individual's utility function. Both are underlying factors developed over time and affected by the socioeconomic characteristics and particular experiences of each. Gathering those constructs can be possible through the inclusion of attitudinal and perceptual questions on a semantic scale in surveys, which also can help to explain the decision-making process carried out in a state preference (SP) experiment. Answers to those additional questions represent observable variables that are indicators of the latent constructs, which are manifestations of the underlying LVs.

Regarding the nature of the phenomenon studied, risk perception, safety culture, and confidence on ERSs are latent constructs that seem to play an important role capturing people's heterogeneity for the estimation of DCFs. For instance, risk perception is a subjective variable and a social and cultural construct. It can be understood as a subjective assessment of being affected by something (Sjöberg et al. 2004). According to Zhang et al. (2011), risk perception to some extent can show the level of a person's risk awareness and act as a mediator between knowledge and behavioral factors. This psychosocial construct focuses on the individual perspective concerning hazards that are prevalent in a particular society at a certain time. People usually evaluate risk and make decisions about their whole life situation (Douglas and Wildavsky 1982; Stave 2005).

On the other hand, safety culture is the attitude, beliefs, perceptions and values that people share about safety in an establishment. Safety culture is a positive value; it prevents injuries, saves lives, and improves productivity and outcomes (Hill Jr 2012). Safety culture is difficult to measure in a direct form; however, it can be observed through indicators related to current people safety performance, such as availability of first aid equipment, empowerment in times

of crisis, and the ability to overcome emergencies and safety behavior. All of these indicators must be able to focus on the positive side of safety - on the presence of something (Hollnagel 2008; Rollenhagen 2010).

The confidence on ERSs depends on their performance. It is a subjective assessment that people make in a specific place according to some aspects. Examples of them are the size and structure of emergency teams, the presence of on-site medical facilities, the temporary coverage of the service offered by emergency groups, the emergency teams preparedness, the interaction of people with local emergency services and the emergency alert system implemented, among others.

The inclusion of latent variables into the HLVDKM depends on using an efficient set of indicators for them. A novel set of indicators for the previous three mentioned LVs was used based on results from a small qualitative study performed before the stated choice experiment. Such indicators are perception and attitude variables with different levels according to the Likert scale (Likert 1932). Each Likert item presents a statement regarding the latent variable, followed by ordered response categories. Respondents were asked to select the category that best reflected their reaction to the declaration. Eight indicators were included, with five levels (e.g. never, seldom, sometimes, often, usually) and binary response options (Yes or No) for two indicators (I4, I8) were included, as presented in Table 11. The Appendix 3 shows the questions presented to the respondents related to each indicator.

Table 11. Latent variable indicators and levels

Latent variable	Type	Indicator	Description	Levels
Risk perception	Perception	<i>I₁</i>	Vulnerability awareness	5
		<i>I₂</i>	Risk awareness	5
		<i>I₃</i>	Awareness of priority needs	5
Safety culture	Attitude	<i>I₄</i>	Availability of first aid equipment	2
		<i>I₅</i>	Empowerment in crisis times	5
		<i>I₆</i>	Ability for overcoming emergencies	5
		<i>I₇</i>	Safety behavior	5
Confidence on ERSs	Attitude	<i>I₈</i>	Contact information with the ERSs	2
		<i>I₉</i>	Genuine connections with ERSs	5
		<i>I₁₀</i>	Responsiveness of the ERSs	5

These indicators are not explanatory variables; instead, they are endogenous to the LVs. The distribution of the answers gathered about the LVs' indicators showed a notable balance between the individuals' preferences. Only the indicators I1 and I3 showed a market trend toward choosing the level "5" (see Figure 13), which can be related to the previous disasters experiences of respondents since 64% of them had been previously impacted.

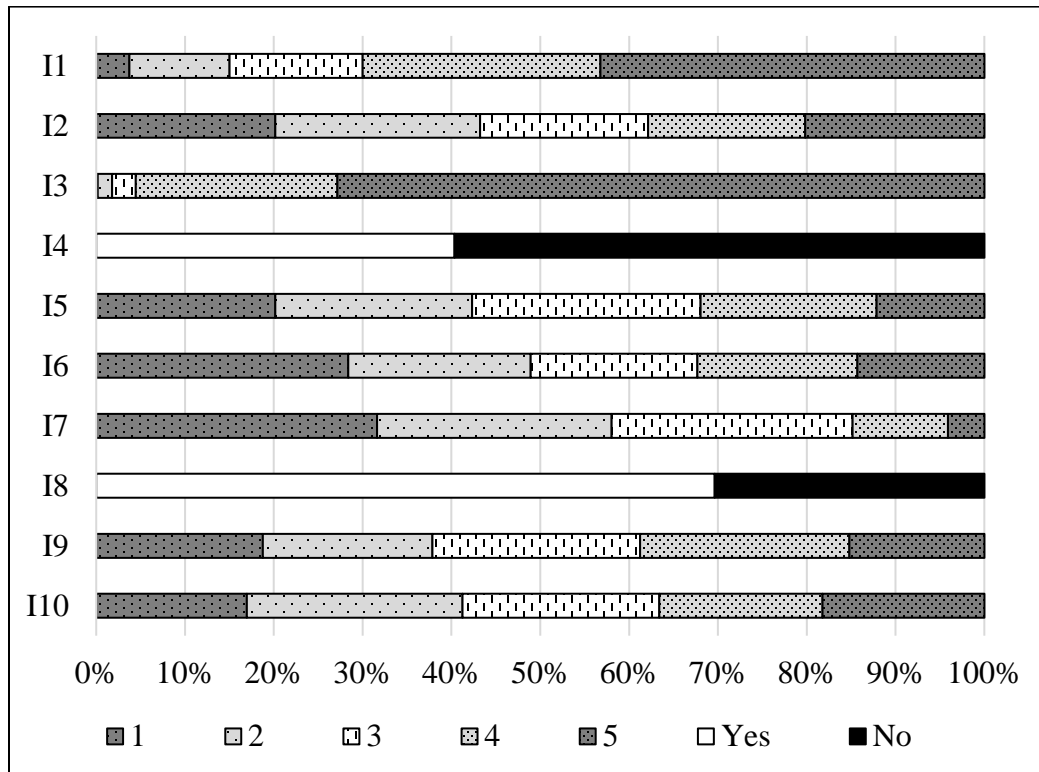


Figure 13. Rate of the LVs indicators

These results conjoint to the data collected from the SC experiment presented in section 3.3 were used for estimating HLVDCEMs using the Simulated Maximum Likelihood Estimation (SMLE) method. The modeling effort is reported in the next section.

5.3. Models Specifications with Latent Variables

The modeling of DCFs considered main variables (e.g. time, price and budget) and socioeconomic (e.g. gender and age) variables as used in chapter 4. However, It was hypothesized that incorporating subjective factors associated with attitudes and perceptions as well as other psychosocial components may influence the behavior of those affected by disasters. The use of HLVDCEMs that simultaneously incorporate the effect of these

subjective factors as well as other objective variables constitutes a good alternative to understanding the people's behavior when they face humanitarian crises. Besides, this analytical framework allows having a better accuracy about the social impacts generated by the humanitarian relief operations.

In this regard, hybrid models expound the analysis of underlying psychosocial factors to obtain information about individual behavior that cannot be explained from the stated or the revealed preferences (Ben-Akiva and Boccara 1987; Walker 2001). Thus, in the integrated model, it is possible to include the attitudes, preferences, and perceptions as psychometric LVs, so that not only the understanding of individual behavior is clearer, but also the predictive power of the model is improved. (Daziano 2012).

The hybrid choice model presented in this chapter consists of a DCM and an LVs model. Both models include structural and measurement equations. Figure 14 shows the general diagram, where ellipses represent LVs, since they are unobservable to the analyst while rectangles represent observable explanatory variables, including characteristics of the individual and the attributes of alternatives (Walker 2001). Dashed arrows represent measurement equations while solid arrows represent the structural equations. The latent variable model describes the relationships between the LVs and their indicators and causes, while the DCM explains the chosen alternative (Vredin Johansson et al. 2006). In this framework, as well as in random utility models, the individual's utility for alternative j (U_{nj}) is considered a latent variable. Finally, the HLVDPCM allows to model the LVs that influence the choice process.

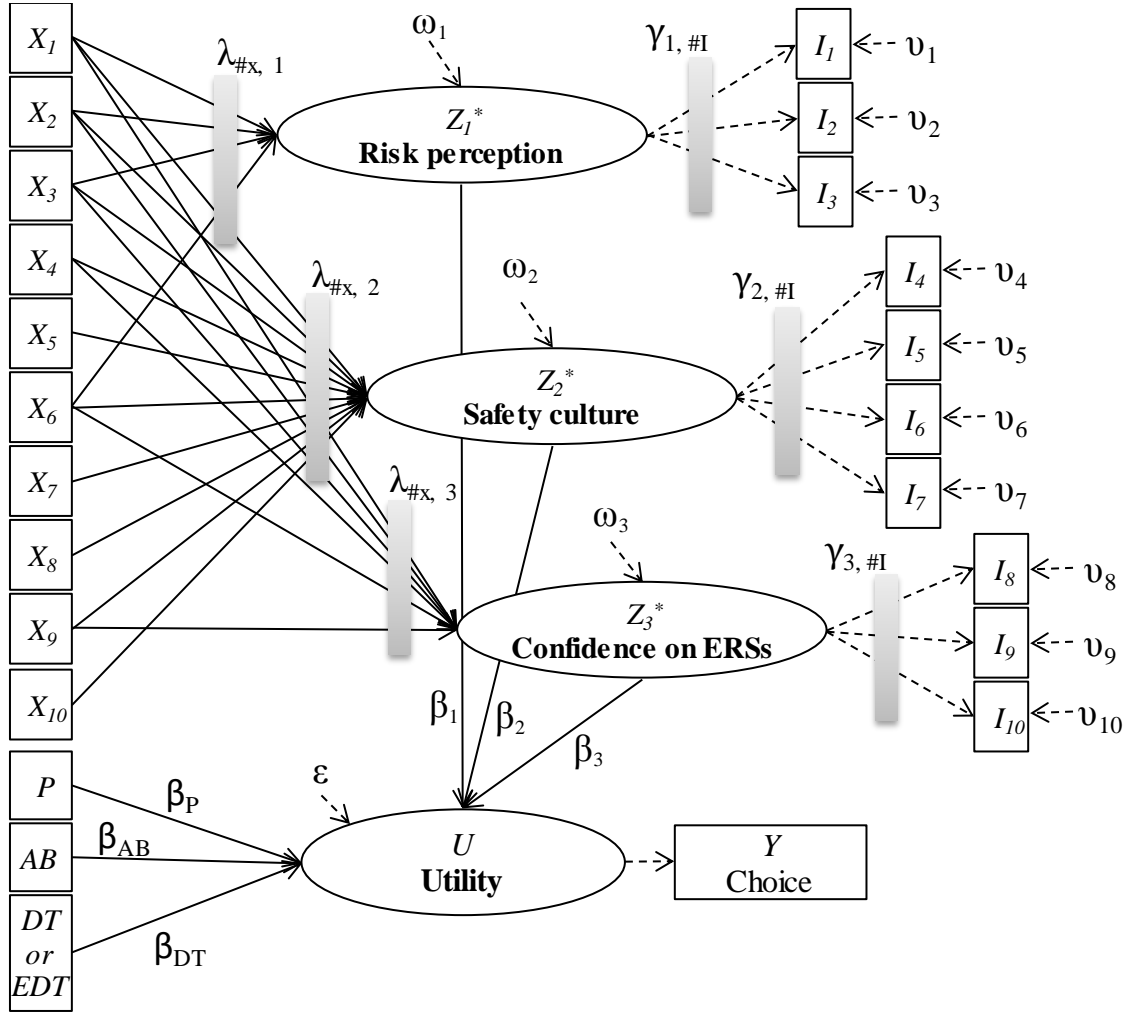


Figure 14. Integrated choice and latent variable model

The notation used in the HLVDLM is as follows:

Z_{n1} : Latent Variable "Risk perception" of individual n

Z_{n2} : Latent Variable "Safety culture"

Z_{n3} : Latent Variable "Confidence on ERSs"

Y_{nj} : Choice indicator takes the value of one for the chosen alternative, zero otherwise

X_{n1} : 1 if individual n has previous experiences in disasters

X_{n2} : Age (More than 50)

X_{n3} : 1 if the individual is female, 0 otherwise.

X_{n4} : 1 if the individual reached a high school diploma, 0 otherwise.

X_{n5} : 1 if the individual has a college degree, 0 otherwise.

X_{n6} : 1 if the individual is an employee, 0 otherwise.

X_{n7} : 1 if the individual is an independent worker, 0 otherwise.

X_{n8} : Household size

X_{n9} : 1 if the household has low income, 0 otherwise.

X_{n10} : 1 if children are living at home, 0 otherwise.

P, AB, DT, EDT : Variables according to the experimental design

λ, γ, β : Parameters of the model to be estimated.

ω, ε, v : Random error terms.

I_n : Choice's indicators according to Table 11.

In the MIMIC model, the structural equations were linear, and the measurement equations were of the ordered Logit type (Greene and Hensher 2010).

5.3.1. Structural Equations

It is specified linear equations for each latent variable such, as shown in Equations 25, 26 and 27. For identification issues, the standard deviations of the errors terms was set to one.

$$Z_{n1} = \lambda_{1,1}X_{n1} + \lambda_{2,1}X_{n2} + \lambda_{3,1}X_{n3} + \lambda_{6,1}X_{n6} + \omega_{n1}, \quad \omega_{n1} \sim N(0, \sigma_{\omega1}^2) \quad (25)$$

$$Z_{n2} = \lambda_{1,2}X_{n1} + \lambda_{2,2}X_{n2} + \lambda_{3,2}X_{n3} + \lambda_{4,2}X_{n4} + \lambda_{5,2}X_{n5} + \lambda_{6,2}X_{n6} + \lambda_{7,2}X_{n7} + \lambda_{8,2}X_{n8} + \lambda_{9,2}X_{n9} + \lambda_{10,2}X_{n10} + \omega_{n2}, \quad \omega_{n2} \sim N(0, \sigma_{\omega2}^2) \quad (26)$$

$$Z_{n3} = \lambda_{1,3}X_{n1} + \lambda_{2,3}X_{n2} + \lambda_{3,3}X_{n3} + \lambda_{4,3}X_{n4} + \lambda_{6,3}X_{n6} + \lambda_{9,3}X_{n9} + \omega_{n3}, \quad \omega_{n3} \sim N(0, \sigma_{\omega3}^2) \quad (27)$$

It is specified that the systematic utilities of the discrete choice model following a functional transformation on the DT attribute, such as is explained by Cantillo et al. (2017a) and Cantillo et al. (2017b). The same two functional forms used in chapters 2 and 3 were considered in this

chapter again (Exponential and Box-Cox). Both formulations describe a nonlinear structure on DT , such as is explicit in the scientific literature (Cantillo et al. 2017a; Holguín-Veras et al. 2016; Holguín-Veras et al. 2013; Pérez and Holguín-Veras 2015). Although it may be argued that the exponential function would probably be more adequate in this context, the use of the Box-Cox transformation enables the modeler to explore other appropriate functional forms (Gaudry and Wills 1978; Ortuzar and Willumsen 2011).

Other relevant attributes included in the utility function are the unitary price of supplies (P) and the available budget to buy other supplies (AB) as expressed in chapter 3 and 4. Similarly, the deprivation time in the utility function of the purchase option is DT , while for the waiting option is EDT .

Since multiple responses were gathered per individual, a panel effect term was included to capture the correlation among them. The panel error component ζ_n was added into the utilities of each respondent (i.e. error components are common across observations of the same person). These errors were assumed to distribute $N(0, \sigma^2)$, where the standard deviation σ is a common parameter across individuals to be estimated (Cantillo et al. 2007). On the other hand, the error terms ε_{nj} were supposed to distribute IID Gumbel $(0, \sigma_\varepsilon^2)$, yielding a logit-kernel formulation.

Model 1. Exponential

$$V_n(p) = ASC + \beta_P P_n + \beta_{AB} AB_n + \beta_{DT} \exp(\beta_{DT1} DT_n) + \beta_1 Z_{n1} + \beta_2 Z_{n2} + \beta_3 Z_{n3} \quad (28a)$$

$$V_n(w) = \beta_{DT} \exp(\beta_{DT1} EDT_n) \quad (28b)$$

Model 2. Box-Cox

$$V_n(p) = ASC + \beta_P P_n + \beta_{AB} AB_n + \beta_{DT} (DT_n^\varphi - 1)/\varphi + \beta_1 Z_{n1} + \beta_2 Z_{n2} + \beta_3 Z_{n3} \quad (29a)$$

$$V_n(w) = \beta_{DT} (EDT_n^\varphi - 1)/\varphi \quad (29b)$$

5.3.2. Measurement Equations

The model included the formulation of eleven (11) measurement equations, one for each indicator presented in Table 11 ($m = 1, \dots, 10$), and one more for the chosen alternative in the discrete choice model, defined by Equation 31.

$$Y_{nj} = \begin{cases} 1 & \text{if } U_{np}[\textit{Purchase}] > U_{nw}[\textit{Wait}] \\ 0 & \text{Otherwise} \end{cases} \quad (30)$$

The measurement equations were specified following ordinal logit type models considering two categories for the indicators I4 and I8, and five categories for the others indicators (see Table 11).

5.4. Results and Analysis

The hybrid models was estimated using maximum likelihood to obtain the unknown parameters of the integrated model simultaneously but also replicating the individual choices observed and the responses to all the questions presented to the respondents regarding each indicator. According to the literature, the joint estimation of the latent variable model and the random utility model is more suitable since the estimators are both consistent and efficient (Raveau et al. 2010; Walker 2001). However, such estimation process is not simple because it requires complex multidimensional integrals. Moreover, it is necessary to introduce the information provided by the perception indicators since otherwise the model would not be identifiable (Raveau et al. 2010). Therefore, simulated maximum likelihood technique was used to solve this problem by building a joint likelihood function in the OxMetrics™ package.

The estimation process was based on 5,040 observations obtained from 560 individual surveyed. With this dataset, two HLVD CMs were estimated considering the previously described functional forms. In both cases, the heterogeneity was captured through the inclusion of the three discussed LVs. Both models were estimated by extracting 1,000 draws from each random variable (i.e. LVs and panel effect term).

Table 12 and Appendix 4 present the estimation results. Each HLVD CM contains 72 parameters: 8 parameters (β) in the choice model, 20 parameters (λ) in the structural model,

10 parameters (α) in the measurement models and 34 thresholds (τ) in ordinal models that explain the indicators through latent variables. Table 12 shows in its first part the estimated parameters of the choice model, the second part shows the parameters of the structural model, and the last one contains the results of the measurement model. Besides, Appendix 4 shows all estimated thresholds for each indicator. For every estimator, the table presents the respective robust t-value and the models' log-likelihood at convergence. Results show that most of the estimated parameters are statistically significant at least at the 95% confidence and their corresponding signs are consistent with microeconomic theory. Note that the estimated parameters of the available budget and unit price of supplies are in thousands of Colombian pesos, while the time is in hours.

Table 12. Estimated HLVDCMs

Choice model		Model 1 Exponential		Model 2 Box-Cox	
Variable	Description	Est.	Rob. t-value	Est.	Rob. t-value
ASC	Constant	-2.8463	-10.67	-2.8193	-10.48
β_P	Unit price of supplies (Thousands COP)	-0.0158	-4.36	-0.0177	-4.85
β_{AB}	Available budget (Thousands COP)	0.0524	11.70	0.0546	12.00
β_{DT}	Deprivation time (hours)	-2.0748	-5.67	-0.0262	-4.40
β_{DTI}	Exponential time	0.0524	12.12		
φ	Box-Cox Parameter			1.8356	24.94
β_1	Latent variable “Risk perception”	0.3166	2.44	0.3183	2.48
β_2	Latent variable “Safety culture”	0.5678	2.09	0.5716	2.11
β_3	Latent variable “Confidence ERSs”	-0.9206	-5.37	-0.9223	-5.41
σ	Panel effect. Standard deviation	0.2260	0.50	0.2417	0.57
$L(\theta)$	Log-likelihood at convergence	-7923.37		-7914.37	
Structural equations model					
Risk perception (Z_1^*)					
$\lambda_{1,1}$	Previous experiences in disasters	1.7680	7.16	1.7678	7.16
$\lambda_{2,1}$	Age (More than 50)	-0.2748	-1.82	-0.2748	-1.82
$\lambda_{3,1}$	Gender (Female)	0.1750	1.20	0.1748	1.20
$\lambda_{6,1}$	Employee	0.0879	0.59	0.0880	0.59
Safety culture (Z_2^*)					
$\lambda_{1,2}$	Previous experiences in disasters	0.4981	4.33	0.4982	4.33
$\lambda_{2,2}$	Age (More than 50)	-0.0251	-0.19	-0.0248	-0.19
$\lambda_{3,2}$	Gender (Female)	-0.0539	-0.49	-0.0544	-0.49

$\lambda_{4,2}$	High school diploma	0.3794	1.55	0.3802	1.55
$\lambda_{5,2}$	College degree	0.5498	2.12	0.5511	2.13
$\lambda_{6,2}$	Employee	0.4037	2.78	0.4028	2.77
$\lambda_{7,2}$	Independent worker	0.2261	1.54	0.2245	1.53
$\lambda_{8,2}$	Household size	-0.0800	-2.83	-0.0798	-2.82
$\lambda_{9,2}$	Lower classes	-0.2178	-1.80	-0.2185	-1.81
$\lambda_{10,2}$	Children at home	0.1407	2.21	0.1410	2.22
Confidence on ERSs (Z_3^*)					
$\lambda_{1,3}$	Previous experiences in disasters	0.6686	5.90	0.6686	5.90
$\lambda_{2,3}$	Age (More than 50)	-0.2103	-2.13	-0.2098	-2.12
$\lambda_{3,3}$	Gender (Female)	-0.1182	-1.17	-0.1178	-1.17
$\lambda_{4,3}$	High school diploma	0.2892	2.62	0.2898	2.62
$\lambda_{6,3}$	Employee	0.1753	1.48	0.1757	1.49
$\lambda_{9,3}$	Low-Income	-0.2147	-2.05	-0.2138	-2.04
Measurement model					
Risk perception (Z_1^*)					
$\gamma_{1,1}$	Vulnerability awareness	1.4312	5.18	1.4315	5.18
$\gamma_{1,2}$	Risk awareness	0.8423	5.85	0.8423	5.85
$\gamma_{1,3}$	Awareness of priority needs	0.5189	4.43	0.5190	4.43
Safety culture (Z_2^*)					
$\gamma_{2,4}$	Availability of first aid equipment	-0.4695	-4.37	-0.4695	-4.37
$\gamma_{2,5}$	Empowerment in crisis times	4.2547	3.14	4.2530	3.14
$\gamma_{2,6}$	Ability for overcoming emergencies	1.8478	9.09	1.8479	9.09
$\gamma_{2,7}$	Safety behavior	1.1773	7.64	1.1774	7.64
Confidence on ERSs (Z_3^*)					
$\gamma_{3,8}$	Contact information with the ERSs	-0.6431	-5.24	-0.6431	-5.24
$\gamma_{3,9}$	Genuine connections with ERSs	3.4170	3.32	3.4164	3.32
$\gamma_{3,10}$	Responsiveness of the ERSs	2.2714	6.05	2.2716	6.05

According to the values of the log-likelihood at convergence, the Box-Cox model achieved a slightly better fit than the exponential model. The estimate parameters of the choice models show that the price and time-related attributes represent a disutility to individuals. The negative sense of the time parameter indicates that a longer period of deprivation significantly reduces the individual wellbeing. Similarly, an increase in the supply price makes its consumption less accessible and limits access to other essential needs such as medicine, transportation, and communications, among others. Also, people with greater income have a

higher willingness to pay for basic supplies. In other sense, low-income people perceive much greater barriers to emergency preparedness.

Regarding the Box – Cox model, the τ parameter is positive and close to the quadratic potential, which indicates that the DCFs have a monotonically increasing, nonlinear and convex form on the DT, a previously mentioned characteristic of the DCFs. The parameter β_{DT1} , which is positive, also describes a convex behavior for DT in the exponential model.

The people's heterogeneity was captured through the inclusion of the three LVs previously discussed, which are related to observable socioeconomic characteristics of individuals. This approach allows an easier extension of findings to a population, given a known distribution of socioeconomic variables. Overall, all estimated parameters of the LVs are statistically significant at the 95% level, and all LVs are in agreement with prior expectations. Unlike the LV Confidence on ERSs, the marginal utilities of the LVs Risk perception and Safety culture are positive. These results are consistent with the theory since the rational and expected behavior of individuals is that their utility increases as their risk perception and safety culture improve. This result also reflects the fact that the probability of purchasing a basket of foods to cover immediate needs increases when risk perception and safety culture also increase. Also, people with higher confidence regarding ERSs are more prone to waiting additional time to receive free humanitarian aid. As expected, the chosen alternative was also dependent on the people attitudes and perceptions effects (Cantillo et al. 2017a; Cantillo et al. 2017b; Holguín-Veras et al. 2016). These results are significantly informative and show that introducing people's inherent characteristics in the utility function is possible to explain heterogeneity in a straightforward and efficient manner, avoiding formulations that are more complex. Similarly, socioeconomic characteristics and psychosocial factors of individuals are determinant variables of disaster preparedness.

The Figure 15 presents the DCFs resulting of applying the HLVD CM technique and the Equation 10 with the estimated parameters. As done in chapter 3 and 4, the resulting curves were fit using polynomial regression models to create practical equations of DCFs, given the complexity of the logsum. As the model 1 was more convex than the model 2, it was necessary to use a third degree Taylor polynomial for the model 1 while a quadratic polynomial for the model 2. The Adjusted R Square values of 0.998 for the model 1 and

0.999 for the model 2 show excellent fits for the curves. The deprivation cost estimates are similar in both models when the times are up to 24 hours. After that value, the exponential model estimates are higher. The results of the exponential model are more in agreement with those obtained by Holguín-Veras et al. (2016).

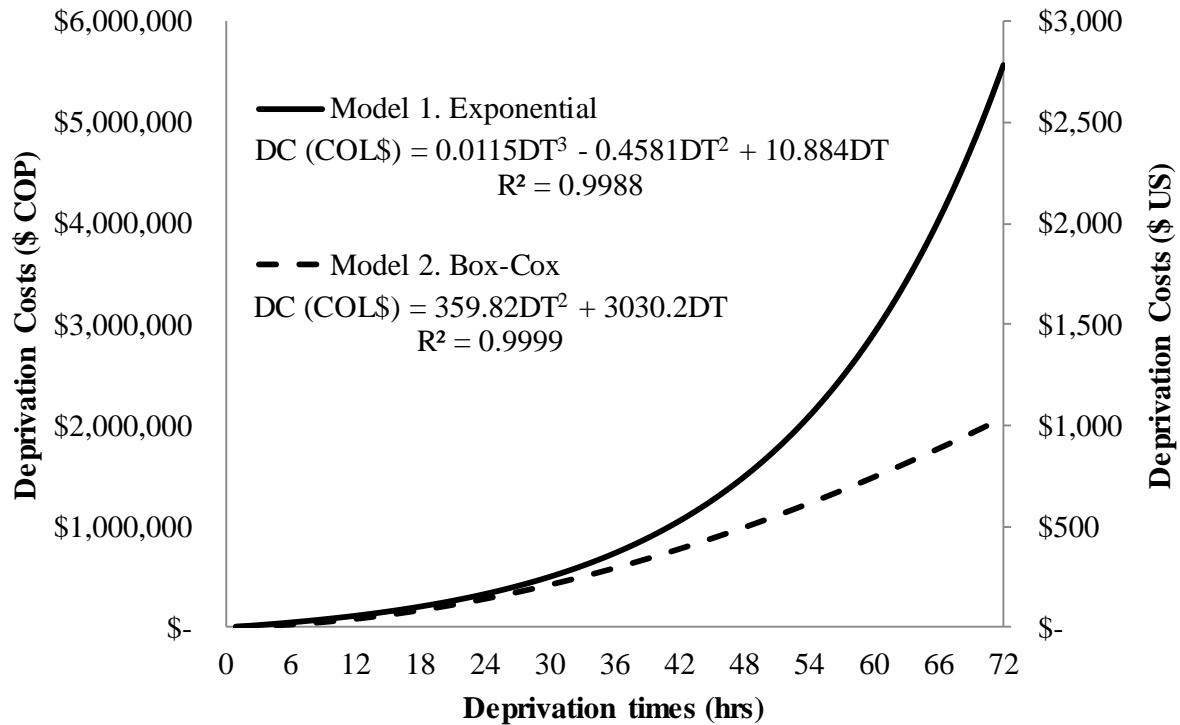


Figure 15. Deprivation cost functions

This DCF exposes the social costs of deprivation, which can be incorporated into comprehensive humanitarian logistics models to perform a risk analysis to evaluate humanitarian aid operations economically. According to the exponential model, after 72 hours of waiting, the deprivation costs are around of US\$ 2,600 per person, far exceeding the results found by others researchers. This deprivation cost will be very close to the value of a statistical life (Márquez and Avella 2012; Rizzi and Ortúzar 2003) the moment at which the individual dies without the help service.

According to the structural model, the results suggest that personal disaster experiences attach great importance to the latent variable “risk perception” presenting a larger marginal

effect when compared to other variables. It is the most statistically significant variable in the structural equations indicating the strong influence that previous experiences in disasters have on the development of people's attitudes towards risk perception. The sense of the sign shows that a greater previous experiences in disasters lead to a better risk perception. Results also suggest that risk perception is lesser for elderly people (people with more than 50 years old), but greater in women compared to men. Both results are consistent with the expected behavior of people and with the literature, which expresses that natural disasters affect women and men in a differentiated way (Iragüen and de Dios Ortúzar 2004; Noland 1995a; PAHO 2012a). Although natural disasters affect all of the population, there are differences in the cultural and physical conditions that can be more evident after a natural disaster (PAHO 2012a).

The structural model of the LV "safety culture" offers significant information about the socioeconomic characteristics of individuals that favor this kind of attitude. Although people may adopt similar codes of conduct and perceptions, not everyone responds in the same way in any given situation. According to the results found, previous experiences in disasters, higher levels of education and employment level and having children living at home lead people to have greater levels of "safety culture" behavior, as expected. The safety culture of an institution is a reflection of the actions, attitudes, and behavior of its members concerning safety. Safety culture emanates from ethical, moral, and practical considerations, rather than regulatory requirements (Hill Jr 2012). In this sense, organizations, and public or private institutions have an ethical responsibility to implement appropriate policies promoting safety culture. They should also have the responsibility of teaching the benefits of having positive attitudes toward safety.

Another important factor influencing the safety culture behavior is the presence of children living at home (Basolo et al. 2009; Eisenman et al. 2009). This last variable, as well as having household members with disability conditions or requiring special health equipment, also increases the likelihood of preparedness to face disasters (Ablah et al. 2009; Eisenman et al. 2009; Hoffmann and Muttarak 2015). In contrast to the previous results, bigger families lead to a lower safety culture behavior. The same tendency was observed for low-income individuals. The last result is explained because low-income classes have less opportunities

to access elevated levels of education and employment. As a result, their safety skills are weak. On the other hand, the size of the household is negatively correlated with income.

The structural model of the LV “Confidence on ERSs” indicates that disaster experience and education are key factors for developing confidence on ERSs as well as individual disaster preparedness, which is also demonstrated by Hoffmann and Muttarak (2015). Contrary to this, results indicate that older adults and the lower classes experience less confidence on ERSs. It is an expected behavior because it is clear that such factors can inhibit individuals to take actions on preparedness to face emergencies.

Regarding the measurement model, all indicators used to explain the LVs considered are statistically significant at the 95% level and they are conceptually valid according to the microeconomic theory. Results show that the latent variable “risk perception” is manifested through the indicators vulnerability awareness, risk awareness, and outreach of priority needs. The first one seems to be more crucial in the representation of risk perception due to a higher value of the estimated parameter. Risk perception is better explained when people are aware of the hazards and perceive them as critical or salient issues within their community. The indicators in the measurement model also suggest that empowerment in crisis times, the ability to overcome emergencies and safety behavior are evidence of safety culture behavior. The confidence on ERSs is captured when people have genuine connections with ERSs and when the responsiveness of the ERSs have a high level of acceptance. Finally, results indicate that when people have many ways to create a connection with the ERSs is because their confidence on a certain and prompt assistance from the ERSs is not well perceived.

5.5. Conclusions

This chapter uses the Hybrid Latent Variables - Discrete Choice Modeling approach to study the influence of personal attitudes and perceptions on an individual’s disaster preparedness. Also, the chapter explores the relationship between these psychosocial factors and the socioeconomic characteristics of individuals. Such attitudes and perceptions were included as explanatory variables into the estimation of DCFs. As a result, two HLVD CMs with different functional forms were estimated using stated preference data. The models allow

constructing DCFs with a monotonically increasing, nonlinear and convex form on the DT, which indicates that a longer period of deprivation significantly reduces the individual wellbeing.

During the first 24 hours of DT, the Box-Cox model provides similar estimates than the exponential model. However, from then on, the exponential estimates are much higher, showing a greater convexity. At 24 hours, the exponential model provides estimates of the deprivation costs close to US \$1,500, well above the market value, which is near US \$5. This fact demonstrates the high relevance of the deprivation costs, which can be much greater than logistic costs.

This work demonstrates that the attitudes and perceptions related to risk perception, safety culture, and confidence on ERSs, play a major role in an individual's disaster preparedness and capturing a population's heterogeneity for the estimation of DCFs. The estimated models lead to the conclusion that personal disaster experiences, as well as socioeconomic characteristics of individuals, are determinant on the development of personal attitudes towards risk perception, safety culture, and confidence on ERSs. The results also suggest that the elderly perceive a lower level of risk than young people. However, women have greater risk perception than men. Individuals with higher levels of education and employment seem to behave better regarding safety culture as well as people having children living at home. Additionally, older adults and members of the lower social classes experiment less confidence on ERSs because they experiment greater barriers to emergency preparedness. All efforts developed in chapters 3, 4 and 5 to measure the impacts of aid distribution process after disasters are consolidated in the next chapter.

6 ASSESSING VULNERABILITY OF TRANSPORTATION NETWORKS FOR HUMANITARIAN RELIEF OPERATIONS

6.1. Introduction

As discussed extensively in Chapter 1, a comprehensive analysis of transportation network vulnerabilities for disaster response must be done base on social costs, such as is suggested by Holguín-Veras et al. (2013) and Pérez-Rodríguez and Holguín-Veras (2015). In a disaster context the impacts of the relief effort on the beneficiaries cannot be assessed using logistics costs since the economic markets where supplies and services are normally traded are not likely to be functioning (Holguín-Veras (2016). In such conditions, humanitarian aid becomes the only alternative to the affected people. As a result, the impacts of the transactions involving relief supplies become externalities that must be captured in social costs (Varian, 1992; Holguín-Veras et al., 2013, 2016). The inclusion of these costs into the analysis will lead to equitable minimization of people' suffering, thus reaching a social optimum level.

Consequently, this chapter presents a vulnerability assessment model of transportation networks for the decision making in humanitarian logistics based on social costs, which is particularly useful for the design and planning of humanitarian resilient supply chains, and to prioritize the access restoration of the post-disaster disrupted network. Such social costs include the logistics cost associated with the relief distribution and the impacts of the relief effort on the beneficiaries. The impacts on the beneficiaries are measured using the DCFs estimated in chapter 3, 4 and 5. This chapter integrates the previous development in a unique model to measure vulnerability in transportation networks.

The organization of the chapter is as follows: Section 6.2 puts forward the proposed vulnerability model. Section 6.3 evaluates the model implementation through two numerical experiments with different complexities. Section 6.4 applies the model to a real case study

using the Colombian Coffee Zone road network. Finally, Section 6.5 discusses findings and conclusions.

6.2. The proposed Vulnerability Model

This research considers all costs from a system perspective, including the SCs. However, involving SCs to analyze the transportation networks requires the simultaneous use of two different cost structures. On the one hand, the logistic costs (Ω_{ijpgq}) to provide an essential supply g from the node i to an individual q located in node j through the path p . This cost depends on the unitary transportation costs of the supply g through each link a that belongs to the path p , C_{agq} . On the other hand, the deprivation costs (γ) experienced by the individual q concerning to the essential supply g , which has a nonlinear structure that depends on a vector of parameters θ , also depends on its socioeconomic characteristics, Z_q , and the total service time, δ . Mathematically (Holguín-Veras et al. 2013), the SC that arises from attending the individual q on the destination j from the source i using the path p is:

$$SC_{ijpgq} = \Omega_{ijpgq} + \gamma_{ijpgq} \quad (31)$$

Where $\Omega_{ijpgq} = \sum_{a \in p} C_{agq}$, and $\gamma_{ijpgq} = \gamma_{ijpgq}(\theta_{gq}, Z_q, \delta_{ijpg})$. As C_{agq} refers to the unitary cost of supply g , by individual q , through link a , computing total costs requires the summation among the individuals. Thus, the total SCs from i through the path p to meet a homogeneous population π_{ijgp} located in j an essential supply g , will be equal to the aggregation of individual costs:

$$SC_{ijgp} = \sum_{a \in p} C_{ag} \pi_{ijgp} + \gamma_{ijgp}(\theta_g, \delta_{ijgp}) \pi_{ijgp} \quad \forall g \in G \quad (32)$$

Assuming a homogeneous population π with similar socioeconomic characteristics (i.e. deprivation costs will depend only on deprivation time) is justifiable because, in the aftermath of a large disaster, it is unlikely that relief groups have detailed data about the individuals that need help (Pérez and Holguín-Veras 2015). Nevertheless, it is possible to discretize the population.

Finally, the SCs of the system including all origin-destination pairs and all productos will be:

$$SC_T = \sum_{i \in I} \sum_{j \in J} \sum_{g \in G} \sum_{p \in P} \sum_{a \in p} C_{ag} \pi_{ijgp} + \sum_{i \in I} \sum_{j \in J} \sum_{g \in G} \sum_{p \in P} \gamma_{ijgp} (\theta_g, \delta_{ijgp}) \pi_{ijgp} \quad (33)$$

Where P is the set of all paths p connecting the origin-destination pair ij , and G is the set of essential goods to be supplied. In Equation 33, the LCs through each path are separable for each network's link. However, DCs do not have this feature since they depend on the total time through every road linking the origin-destination pair ij . DCs can not be associated with each link due to their nonlinear and convex structure over time. It is a key feature that increases the complexity of incorporating time dependent effects into SCs functions.

To deal with this matter, The authors use DCFs arising from the total travel time from every origin i (supply nodes-SN) to each destination j (demand nodes-DN) for each one of the (reasonable) paths that belong to the access route tree of each origin-destination pair, w . Such paths comprised reasonable arcs that allow to simplify the combinatorial problem associated with the network density, which is NP-hard problem. To identify each reasonable arc, the authors implemented a similar procedure to Dial (1971), in which a reasonable link is one which does not backtrack. That is, a path is reasonable if every link in it has its terminal node closer to the destination than its initial node. As it progresses from node to node, it always gets closer to the destination. The authors implemented this procedure to obtain subsets (sub-branches) of reasonable paths between each origin-destination pair. This choice set contains all feasible alternatives whose choice probability is different from zero. All reasonable paths with equal SC will have the same chance of being used. If there is more than one reasonable path between each origin-destination, the one with lower SC has the highest probability to be used. In consequence, the criticality of a network link (Jaller et al. 2015) depends on its impact on SCs when disrupted, which depends largely on accessibility to the area. For instance, the lower the accessibility, the greater the delay in the attention process thus increasing the SCs.

Each path p from the choice set is associated with a level of utility. The modeler, an observer of the system, only knows some elements considered by the decision maker, so he or she assumes that the decision maker's utility has two elements (see Equation 1). First, a systematic utility function, V_{ijgpq} , which is a function of the SCs of the reasonable path, p , which belongs to the choice set. The second element is a random error term, ε_{ijgpq} , which

reflects any observational errors made by the modeler (McFadden 1973; Ortuzar and Willumsen 2011; Train 2009b; Williams 1977). The utility was associated to the social costs, according to Equation 34.

$$V_{ijpgq} = (\Omega_{ijpgq} + \gamma_{ijpgq}) \quad (34)$$

The decision maker chooses the alternative that provides the greatest utility. If the error terms distribute identically and independently (iid) Extreme Value Type 1, EV1, the probability that the decision-maker chooses the alternative, p , from his/her available choice set, P , could be modeled using the the multinomial logit (MNL) model (Domencich and McFadden 1975):

$$P_{ijpgq} = \frac{e^{(-\mu V_{ijpgq})}}{\sum_{p \in P} e^{(-\mu V_{ijpgq})}} \quad (35)$$

The parameter μ is a dispersion factor which is related to the common standard deviation of the EV1 variate by $\pi/\sigma\sqrt{6}$ (Ortuzar and Willumsen 2011). As μ is nonnegative, the probability of using a particular path is directly proportional to $\exp(-\mu V_{ijpgq})$. Where μ must be calibrated to represent the system's behavior better.

The modeler observes V_{ijpgq} and knows the distribution of the remaining portion of the utility. Consequently, the expected consumer surplus (CS) is a function of the decision-maker's utility (See Equation 9), which in a logit model is the log of the denominator of the choice probability. The expectation is over all possible values of the ε_{ijpgq} (Williams 1977). Such expression is often called “*the log-sum term*” and in the context of this research is equivalent to the Expected Social Costs (ESCs) of humanitarian assistance for an affected individual q . The authors evaluate the ESCs for each origin-destination pair considering all alternatives of the choice set.

Traditionally, the social assessment of transportation projects uses the log-sum term because it allows obtaining the benefits that travelers experience due to changes in costs and travel times (De Jong et al. 2007; Erath 2011). Consequently, the log-sum term is an appropriate econometric term to assess the impact that a certain disruption on the network has on the whole system. The economic impacts for any origin-destination pair would be the difference

between the logsum before and after the disruption scenario (see Equation 10) (Erath 2011; Williams 1977). The Equation 10 estimates changes in CS with a measurement unit (e.g., hours or dollars) depending on the choice of μ (Train 2009b). Where the superscripts 0 and 1 refer to a disruption scenarios before and after. The total impact $\Delta E(CS_{ij})$ is the summation on the set of essential supplies G and on the population in j attended from i .

As a result, the authors constructed a vulnerability indicator of the network for the disruption scenario s , I_s , using Equation 36. The numerator is the change in CS as explained in Equation 10, and the denominator is the expected consumer surplus before the disruption scenario. Each OD pair has a weight φ_{ij} that reflects its significance when compared to the other pairs. As a proxy for this weight, the model considers the affected population at j that will be served from the origin i , assuming that the affected people have the same level of deprivation time.

$$I_s = \sum_{i,j} \frac{\Delta E(CS_{ij})}{E(CS_{ij})} \varphi_{ij} \quad \forall s \in S \quad (36)$$

Previous works have assumed S different disruption scenarios that can affect both the capacities of the links on the network as well as demands. However, the selection process of those disruption scenarios is not a trivial task. It is a combinatorial problem, commonly known as NP-hard problem due to the large number of possible states that must be considered for practical networks with many nodes (Gómez et al. 2013). The scientific literature offers some alternatives: (1) full or partial closure, one by one, of each link in the network (Balijepalli and Oppong 2014; Chen et al. 2007; Chen et al. 2012; Jaller et al. 2015; Luatthep et al. 2013; Qiang and Nagurney 2008; Scott et al. 2006; Sohn 2006; Sullivan et al. 2010; Taylor and D'Este 2005); (2) full or partial closure of links randomly chosen (Jenelius et al. 2006); (3) full or partial closure of those links that, according to the researcher's judgement, have the greatest system impacts (Agarwal 2011); and (4) associating a closure probability to each link or link group (Dehghani et al. 2014; Jenelius 2009; Jenelius 2010; Jenelius and Mattsson 2012; Qiang and Nagurney 2012). Other approaches involving heuristics and metaheuristics include methods such as network clustering which can simplify the network density by using fictitious nodes (clusters) and fictitious links (link arrangements) at different levels of abstraction (Gómez et al. 2011; Gómez et al. 2013).

In this work, the authors designed the disruption scenarios following a two-stage process. First, each link in the network is independently fully disrupted, obtaining a I_s for each link. Second, a computer algorithm in MatLab ® (see Appendix 5 for pseudocode) was developed in this doctoral thesis to construct the most critical scenarios considering all possible combinations of those links with the highest I_s .

It is important to highlight that natural disasters are low-probability events that can cause large losses when they occur (Cavallo and Noy 2009). Although disruptions to several links can happen, the joint disruption probability of several links will be the product of their individual probabilities, assuming that they are independent events. Therefore, disruption scenarios involving many links have lower probabilities than those with a small number of links.

In general terms, the proposed model considers a series of assumptions about initial operating conditions such as the risk level for each zone of the territory, information about road conditions, the location of disaster response facilities, and critical supply forecasts at the network nodes with the highest levels of risk. The proposed approach does not consider congestion phenomenon. This is because, although disaster recovery activities and processes such as material convergence (Holguín-Veras et al. 2014; Jaller 2011) could generate congestion in the impacted areas during the post-disaster phase, there is an expected interruption of the normal day-to-day activities in the system. That is, the population may temporarily suspend daily trips for work, study, pleasure, shopping or personal errands. Public transportation may be paralyzed, as well as freight transportation due to the interruption of the commercial markets (except aid distribution) (Holguín-Veras et al. 2012b; Holguín-Veras et al. 2013; OPS 2000; OPS 2001). Consequently, drastically reducing the normal flow of cars, buses, and trucks. Also, people have uncertainty about the state of the infrastructure, which obviously affects its use (Holguín-Veras et al. 2012b).

The implementation of the proposed model involves the following steps:

1. *Estimating travel times for reasonable paths.* Determine the subset of reasonable paths connecting each origin-destination pair and corresponding travel times considering initial design and system conditions;
2. *Determine the SC for every reasonable path.* That is, evaluating the DC using the corresponding DCF on the travel time for each road and adding the LC of the distribution operations;
3. *Estimate the log-sum term.* For each subset of reasonable paths between each origin-destination pair;
4. *Generate the set of disruption scenarios D ;*
5. *Repeat steps 1-3.* For each scenario $d \in D$;
6. *Estimate vulnerability indicator.* Use Equation 9 for all origin-destination pairs on the network and normalize the results according to Equation 36 to obtain the vulnerability indicator for each disruption scenario (I_s).

6.3. Numerical Experiments

This section discusses two numerical experiments to show the implementation of the proposed model. The first case (experimental setup I) examines a small network considering a single origin-destination pair to show the benefits of using reasonable paths and the characteristics of the proposed model. The second experiment (experimental setup II) implements the model in a denser network with multiple supply and demand nodes. This case also shows the behavior of the model considering disruption scenarios that include several links. The results compare the use of the proposed model with SCs and with LCs only. Although the proposed model is multi-product, for illustration purposes, the analyzed instances involve a single product.

Both numerical experiments assume known the location of the facilities for humanitarian response, the risk conditions in the area and the topology of the network. Similarly, the experiments assume that the optimal allocation (distribution) of resource and relief strategies

are known (see Pérez and Holguín-Veras (2015)). With these assumptions, the efforts concentrate on estimating the network vulnerability as a measure to plan the resilience of the disaster response logistics operations and access restoration (prioritizing the rehabilitation of the interrupted links) in the post-disaster situations.

As a mathematical construct, the experiments assume the existence of air (transport) bridges (links) between supply and demand nodes which do not get disrupted (to guarantee accessibility). Air links have been used in the past to respond to several rapid onset disasters, like the earthquake in Haiti, the tsunami in Japan, Hurricane Sandy, and the Ebola crisis in West Africa, among others. However, the air link costs are greater than the road ones. In the experiments, they are assumed to be about 15 times over-the-road costs, in line with a market research performed by the authors.

The analyses used one of the DCF proposed and estimated in chapter 2 with data collected about the willingness to pay of people for access to water in a disaster context to estimate the SCs. Although DCs could be a function of individual characteristics (e.g., age, gender, health condition), this model assumes a generic function that depends only on the deprivation time (See Figure 16). This practical consideration is appropriate because it is almost impossible that the relief organizations will have precise data about the socio-economic characteristics of the affected people in the immediate aftermath of a disaster. Additionally, the consideration of socio-economic characteristics based on faulty information could lead to outcomes that unfairly favor some people at the expense of others, which is questionable. On the other hand, the dispersion parameter required in Equation 36 was selected based on the Colombian strategic freight transportation network (Cantillo et al. 2014; Márquez and Cantillo 2013), which was $\mu = 0.426$.

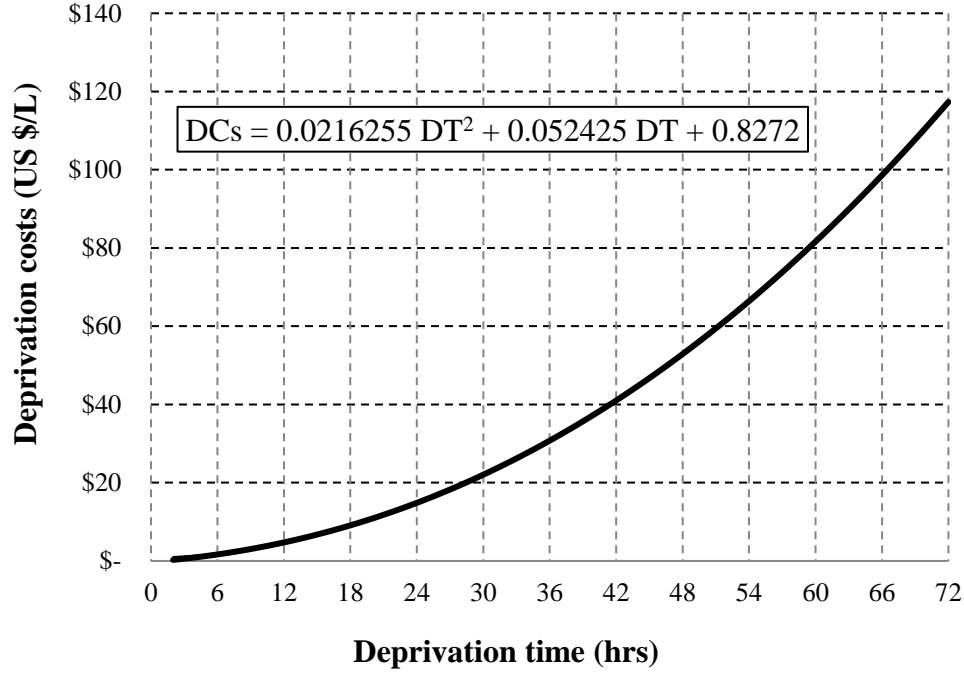


Figure 16. DCF used for network vulnerability model

Source: Exponential Model (Equation 12)

6.3.1. Experimental Setup I: A Small Network With a Single Origin-Destination Pair

Two modes of transportation are considered in this instance (land and air transportation). The network has nine nodes (including a supply node and a demand node), 28 road links (a link for each direction) and a direct air connection between the supply and demand nodes (dotted line) (see Figure 17). The analyses assume that node 9 is vulnerable and, according to the emergency response plan, the aid should be distributed from node 1. The affected population is 500 people in node 9 and the total demand of supply can be satisfied from node 1. The travel time in hours, and the logistics costs to serve a beneficiary (in parentheses) are presented over the links, which are the same for each direction. The whole paths-network (full enumeration) for origin-destination pair 1-9 results in 22 possible access paths, from which eleven make up the reasonable path subset. It is important to highlight that such reasonable paths have the shorter travel times between the origin-destination pair 1-9 and consequently the highest choice probabilities. The reasonable path subset accounts for 98.04% of choice probabilities (see Table 13). Link disruptions can affect multiple paths. For instance, if link 6-9 is interrupted, the reasonable paths 5, 6 and 7 (in Table 13) are also

interrupted, and thus the remaining reasonable paths will be more feasible, which is understood as a resilient network behavior.

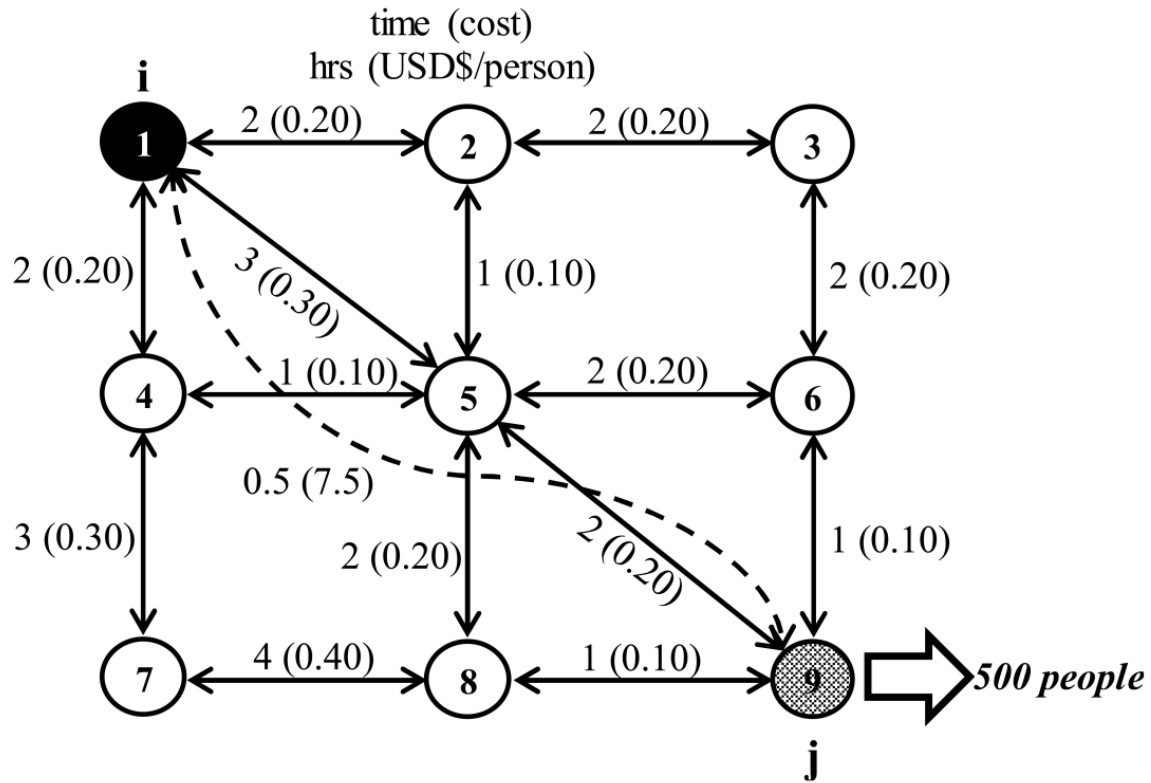


Figure 17. Network Topology in the experimental setup I

The social costs associated with each path (column 8) are obtained by adding the deprivation costs, calculated using the DCF presented in Figure 16 (column 7), with the LCs (column 6). The authors estimated the ESCs of the corresponding origin-destination pair, using the log-sum term for the affected population. Table 14 shows the results after evaluating the disruption of each network link.

Table 13. Results of the experimental setup I

No	Path	Type of path	Mode	Travel time (hrs)	Ω_{ijpq} (\$US/person)	γ_{ijpq} (\$US/person)	SC_{ijpq} (\$US/person)	P_{ijpq}
1	[1,9]	R	A	0.5	7.50	4.29	11.79	4.44%
2	[1,2,5,9]	R	T	5	0.50	8.15	8.65	16.9%
3	[1,4,5,9]	R	T	5	0.50	8.15	8.65	16.9%
4	[1,5,9]	R	T	5	0.50	8.15	8.65	16.9%
5	[1,2,5,6,9]	R	T	6	0.60	9.60	10.20	8.75%
6	[1,4,5,6,9]	R	T	6	0.60	9.60	10.20	8.75%
7	[1,5,6,9]	R	T	6	0.60	9.60	10.20	8.75%
8	[1,2,5,8,9]	R	T	7	0.70	11.27	11.97	4.12%
9	[1,4,5,8,9]	R	T	7	0.70	11.27	11.97	4.12%
10	[1,5,8,9]	R	T	7	0.70	11.27	11.97	4.12%
11	[1,2,3,6,9]	R	T	7	0.70	11.27	11.97	4.12%
12	[1,4,5,2,3,6,9]	NR	T	9	0.90	15.25	16.15	0.69%
13	[1,5,2,3,6,9]	NR	T	9	0.90	15.25	16.15	0.69%
14	[1,2,3,6,5,9]	NR	T	10	1.00	17.57	18.57	0.25%
15	[1,4,7,8,9]	NR	T	10	1.00	17.57	18.57	0.25%
16	[1,2,3,6,5,8,9]	NR	T	12	1.20	22.85	24.05	0.02%
17	[1,2,5,4,7,8,9]	NR	T	12	1.20	22.85	24.05	0.02%
18	[1,5,4,7,8,9]	NR	T	12	1.20	22.85	24.05	0.02%
19	[1,4,7,8,5,9]	NR	T	14	1.40	29.00	30.40	0.00%
20	[1,4,7,8,5,6,9]	NR	T	15	1.50	32.40	33.90	0.00%
21	[1,2,3,6,5,4,7,8,9]	NR	T	17	1.70	39.84	41.54	0.00%
22	[1,4,7,8,5,2,3,6,9]	NR	T	18	1.80	43.89	45.69	0.00%

R: Reasonable path; NR: Non-reasonable path; A: Air; T: Terrestrial (road); Pp: Probability of the path p

The results show that a disruption in link 5-9 leads to an increase of 28.3% in the ESCs of the system, which indicates that this link is the most critical in the network. Such link is part of the reasonable paths subset presented in Table 13 (paths 2, 3 and 4) with the highest probabilities (16.95%), which explain its importance. If the link (5-9) is interrupted, such paths will not be available; therefore, the paths 5, 6 and 7, which are less likely to be used under normal conditions (8.75%), become relevant. Table 14 also shows that some links are not critical for the system since they tend to backtrack, which result in longer travel times.

The ranking presented simplifies the design and planning of humanitarian resilient supply chains over the area.

Table 14. Vulnerability indicators for disruption scenarios in the experimental setup I

Links	I_s	Links	I_s
(5-9)	0.2833	(5-8)	0.0668
(1-2)	0.1623	(8-9)	0.0668
(1-4)	0.1623		
(1-5)	0.1623		
(2-5)	0.1623		
(4-5)	0.1623		
(5-2)	0.1623		
(5-4)	0.1623		
(5-6)	0.1425		
(6-9)	0.1425		

I_s : Vulnerability indicator of the scenario s

6.3.2. Experimental Setup II: A Large Network with Several Origin-Destination Pairs

The authors used the structure of the well-known Sioux Falls network for the second experiment. 24 nodes and 76 links comprise this network. As in the numerical experiment I, times and average costs of travel are known for each network link and nodes in a vulnerable situation (see Figure 18). Table 15 shows the location of the disaster response facilities and the distribution strategy of humanitarian supplies. The strategy indicates that the demand nodes should be served from different supply nodes, as it occurs in reality due to the request of supplies, after catastrophes, often exceeding the locally available resources (Gómez et al. 2011).

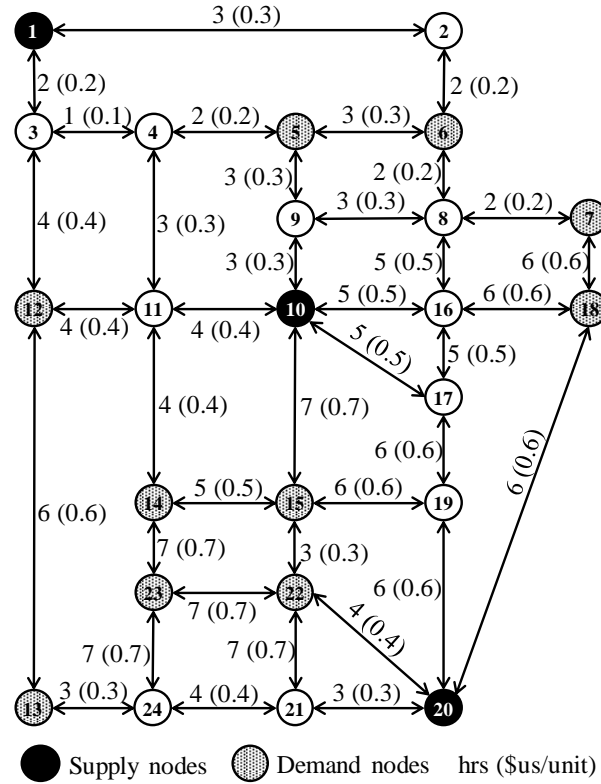


Figure 18. Structure of the Sioux Falls Network

Table 15. Optimal distribution strategy assumed for the experimental setup II

Supply node	Demand node	Air link costs. hrs (\$/unit)	People assisted
1	5	0.5 (7.5)	100
	12	0.6 (9.0)	100
	13	1.2 (18.0)	100
	14	1.0 (15.0)	100
10	5	0.6 (9.0)	100
	6	0.8 (12.0)	200
	7	0.8 (12.0)	200
	12	0.8 (12.0)	100
	15	0.7 (10.5)	100
20	13	1.0 (15.0)	100
	14	1.2 (18.0)	100
	15	0.7 (10.5)	100
	18	0.6 (9.0)	200
	22	0.4 (6.0)	200
	23	1.1 (16.5)	200

Figure 19a shows the ranking of links whose disruption impacts more than 2% of the total system cost considering ESCs. For instance, interruption of the links connecting nodes (20, 22) or (10, 9) increases the system ESCs by 10%. These critical links are included in more than 70% of the reasonable paths connecting the demand and supply nodes.

When comparing the results of the proposed model (Figure 19a) with those obtained using the approach that only considers LCs (Figure 19b), the results evidence significant differences. For example, the traditional model would prioritize the link 20-18, which only increases ESCs by 4% instead of the 20-22 and 10-9 links. It is important to highlight that an increase in the density of the network positively affects the accessibility between the supply and demand nodes, making the disruption of the individual links less important. It explains the difference in magnitude of the impacts between the two numerical experiments.

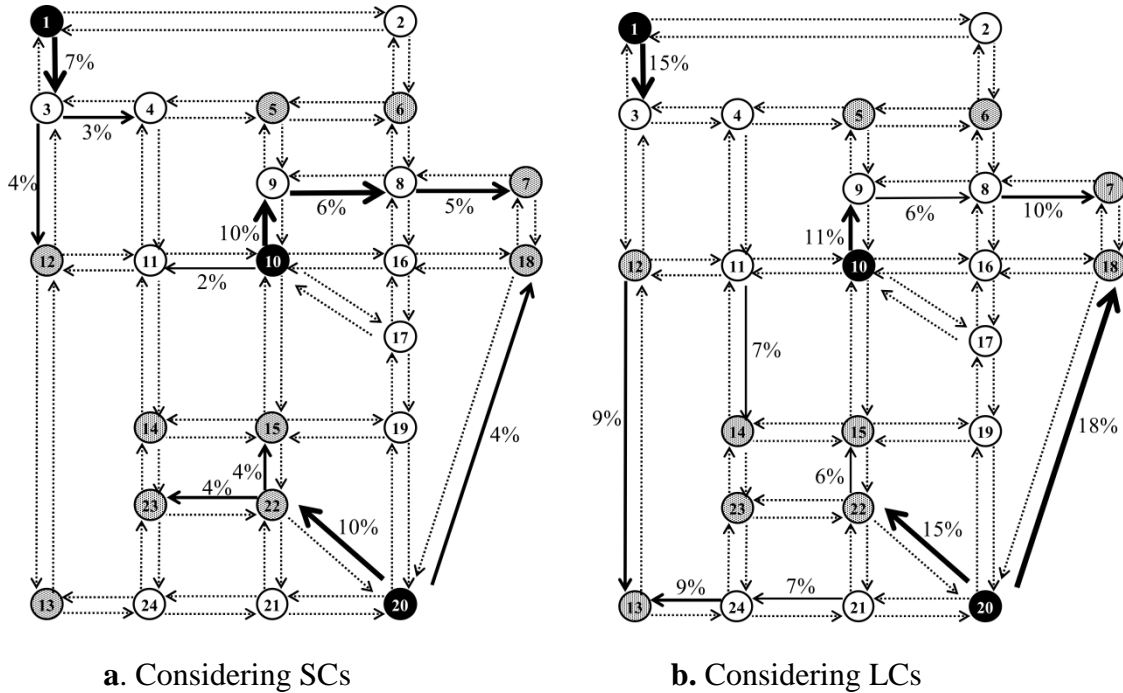


Figure 19. Model results with disruption scenarios of a link in the experimental setup II

Moreover, considering the simultaneous disruption of 2 links in this graph results in 2,850 likely scenarios. Critical combinations, in this case, consider those links that individually have a high impact. Figure 20 shows the most unfavorable combinations of two links. These results can be compared to the critical links from Figure 19a. The analysis also raises an important question regarding the synergy or coupled effect of disrupted link combinations.

Positive synergy occurs when the disruption of different links combined produces a total effect that is greater than the sum of the individual effects.

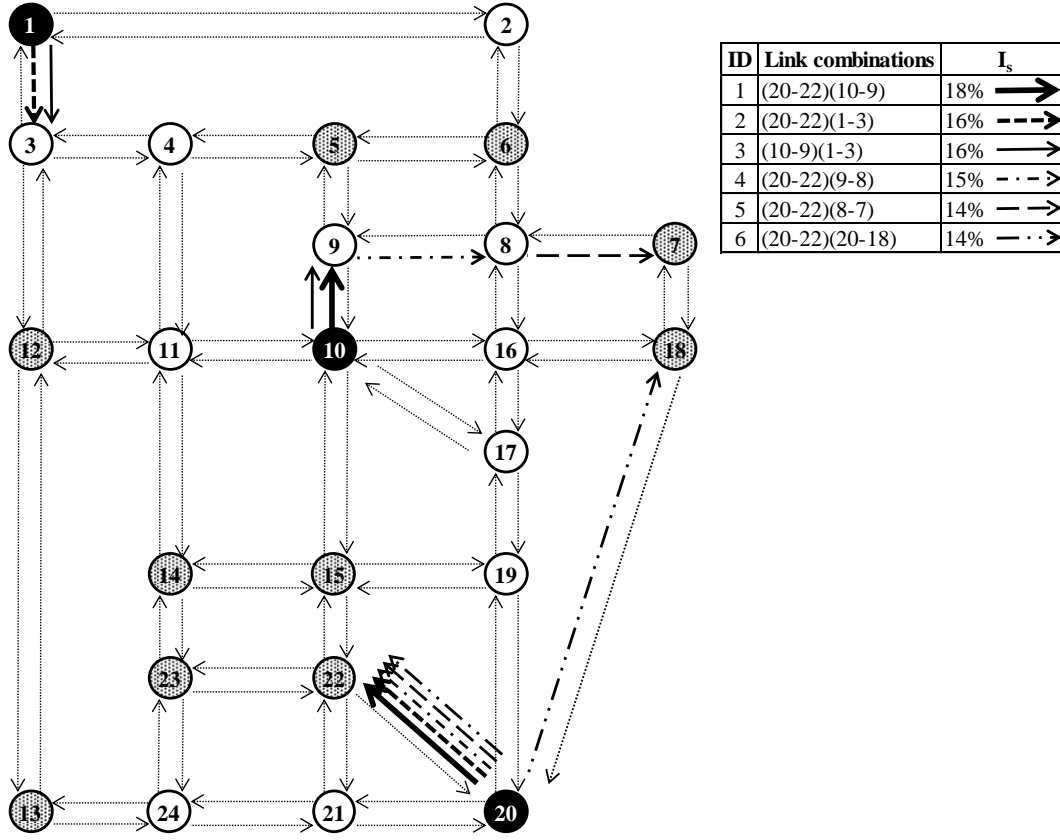


Figure 20. Simultaneous disruption of 2 links in the experimental setup II

Analyzing the synergy of 2-link combinations shows that the sum of the individual effects exceeds the grouped effects in 70% of the scenarios, thus indicating a dominant presence of negative synergy. Consequently, the maximum estimated difference considering positive synergy was 2.56%. Figure 21 shows the difference between the individual effects and grouped critical combinations of two links (The Figure 21 is related to the IDs in Figure 20). The results evidence slightly higher individual effects above the grouped ones. For example, for the most critical combination (ID = 1 with links 20-22 and 10-9), the sum of the individual impacts is 0.20, while the joint disruption of both links results in 0.18.

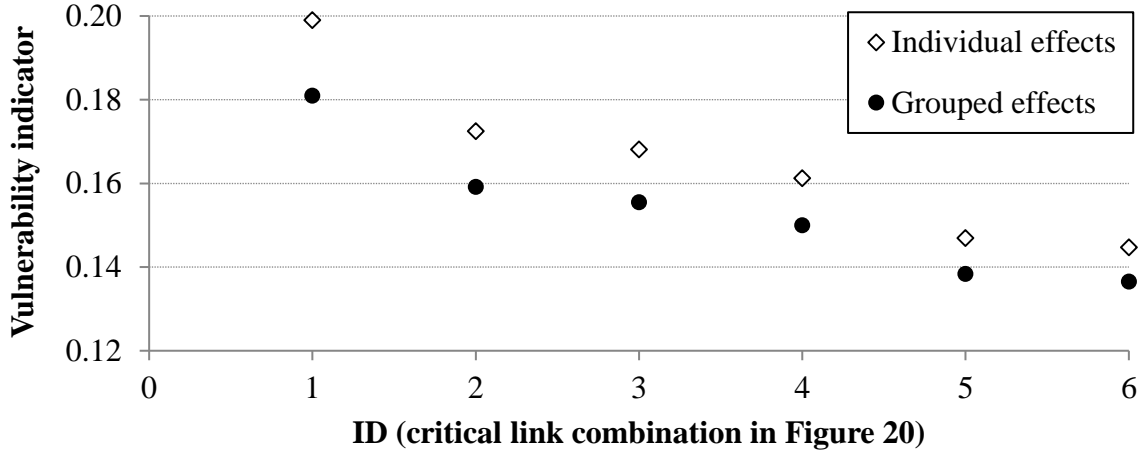


Figure 21. Effect of synergy in critical combinations of 2 links in the experimental setup II

Further experiments evaluated the impact of higher order disruption scenarios. As expected, increasing the number of links within the disruption scenario increased the frequency of negative impacts on upper ranges of vulnerability (See Figure 22). However, the results indicate that even for higher orders, the most critical links (under single link disruption) help explains a significant percentage of the impact contributions. This result is relevant as it helps to simplify the combinatorial problem associated with the generation of the scenarios and facilitates the applicability of the proposed model. Moreover, implementing the model for single links allows generating potential scenarios including higher impact and even worst-case combinations.

As shown in Figure 22, there are 88.16% of single-link disrupted scenarios whose impact on the system is less than 5% while only 1.32% of the scenarios impact in more than 15% the total system costs. If more than one link is considered in a disruption scenario, the network vulnerability increases since the accessibility decreases significantly. On the other hand, the consideration of three impacted links in each disruption scenario leads to an increase of 4.35% on upper ranges of vulnerability (more that 15%). In other words, as expected, the network vulnerability increase as the number of links considered in a disruption scenario increase; however, the magnitude of the marginal effect of new disrupted links depends on how dense the network is.

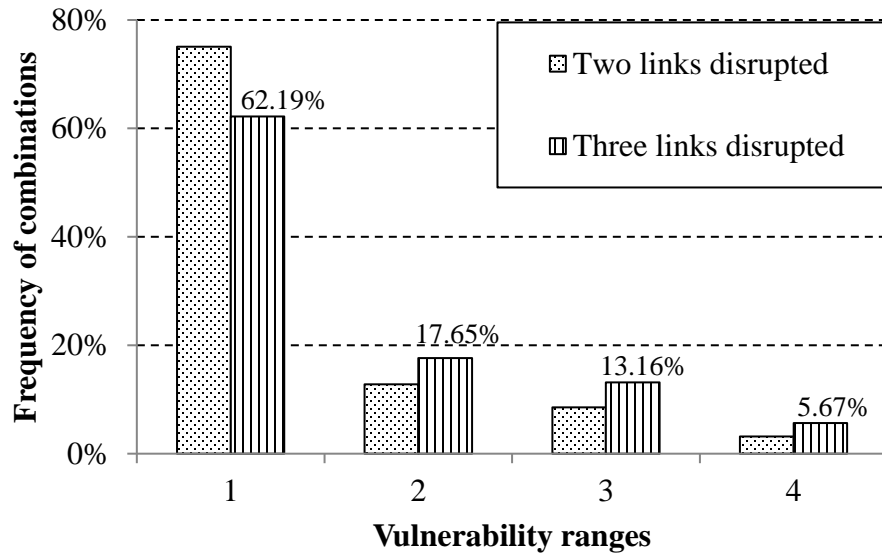


Figure 22. Links Frequency by range vulnerability and disruption scenarios

Although this is a small-scale network, these results could be transferred to highly dense networks (e.g., urban networks), allowing the use of more efficient searching algorithms combined with clustering methods such as the one proposed by Gómez et al. (2013).

An interesting scenario is when there are no available air connections between the supply and demand nodes. In such case, the pattern of critical link combinations presented in Figure 20 will be different, being more critical those road links that allow access to nodes 1, 7 and 13, which have less accessibility (see Figure 23); moreover, the vulnerability indicators of such critical links exceed 90%. For the other nodes, the accessibility is conserved; therefore, the vulnerability indicators of their associated links are under 52%.

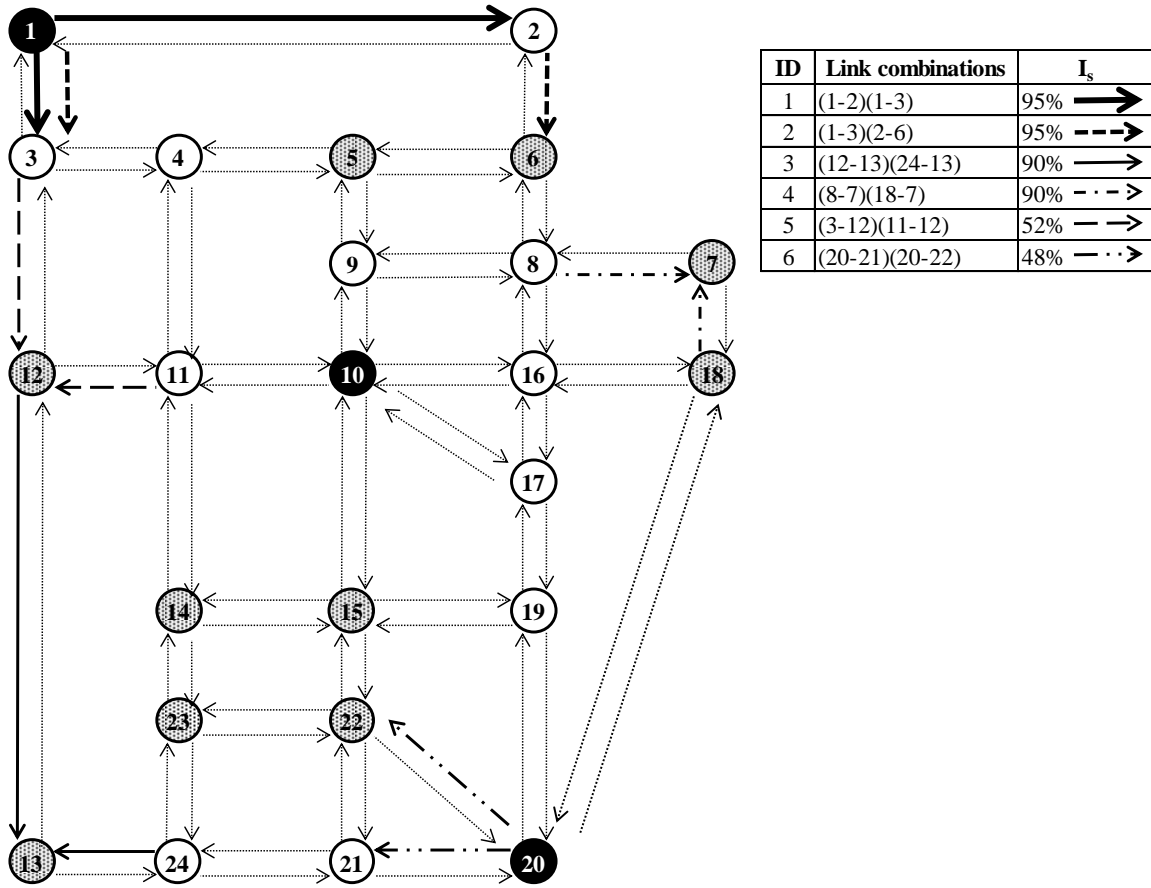


Figure 23. Simultaneous disruption of 2 links without air link connections

6.4. Empirical Analyses: The Colombian Coffee Zone Road Network

6.4.1. Specifications and Data

This section discusses the implementation of the proposed model to evaluate the vulnerability of the Colombian Coffee Zone road network. The study area includes the city of Armenia and 8 municipalities in this region. There is high seismic risk because of the triple junction that occurs at the northwest corner of the South American Plate where the Nazca, Cocos, and Pacific plates converge (Kellogg et al. 1995). The last significant event occurred in 1999, known as the Armenia Earthquake that killed 1,185 people and affected 160,397 (CEPAL 1999). Information about the transportation networks and logistics costs was obtained from the Colombian Strategic Freight Transport Model (Cantillo et al. 2014; Márquez and Cantillo 2013). Meanwhile, information related to the population affected comes from CEPAL (1999).

Figure 24 shows the regional road network with the supply and demand nodes around the study area. The resulting road network topology consists of 29 nodes (including 8 demand nodes and 4 supply nodes) and 43 links. The simulation assumes separated links for two-way road segments and estimates the impacts for each direction separately. The authors used Geographic Information System (GIS) tools to locate every node and link and additional information layers for population socio-demographic variables.

Also, the supply distribution strategy assumes that the supply nodes 1 and 4 serve just 30% of the total demand while the supply nodes 5 and 29 serve the remaining 30% and 40% respectively.

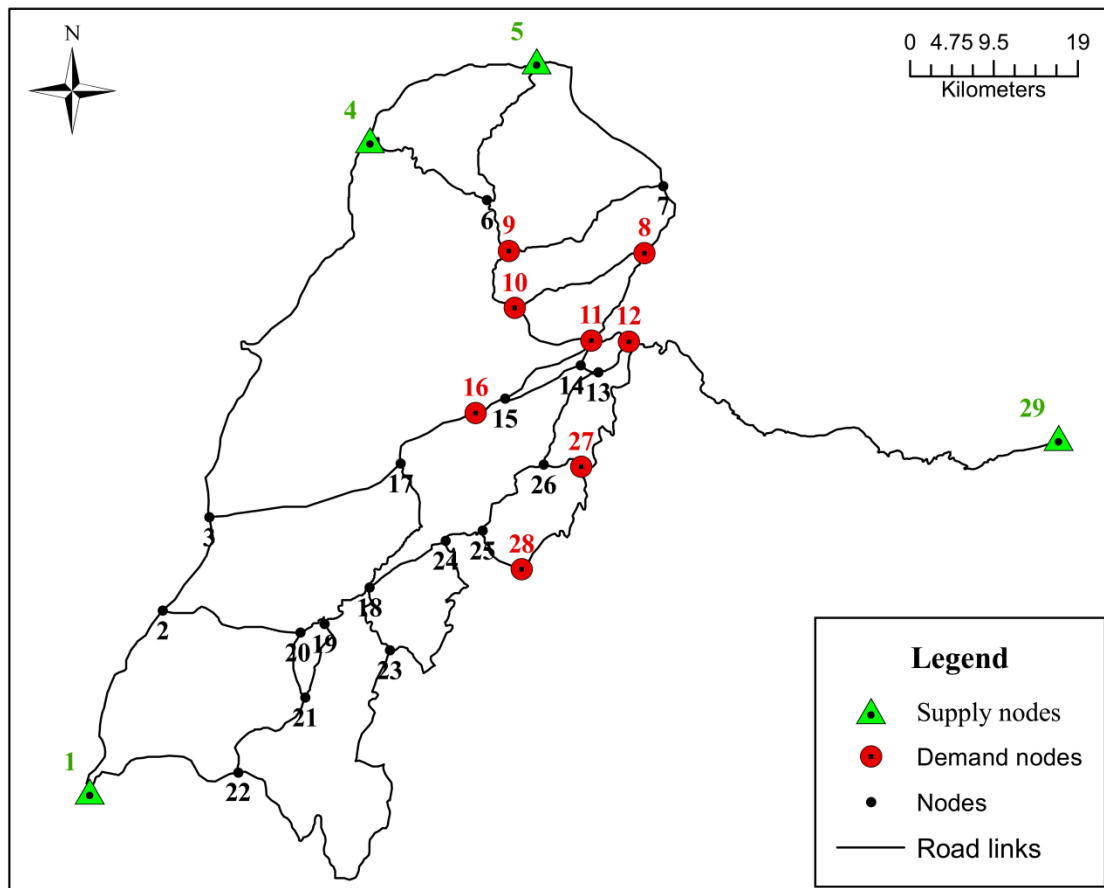


Figure 24. The southwestern Colombia road network

6.4.2. Results

After implementing the proposed model, Figure 25 shows the most critical links for the disaster response logistics operations in the affected area. As expected, the disruption of the

link (29-12) leads to a great ESCs on the system (almost 15%) because it is the only way (no redundancy) to access the affected area from supply node 29. The disruption of this link affects 30% of the demand. Consequently, the system should be planned to account for the vitality of such link or to have an additional supply at other nodes.

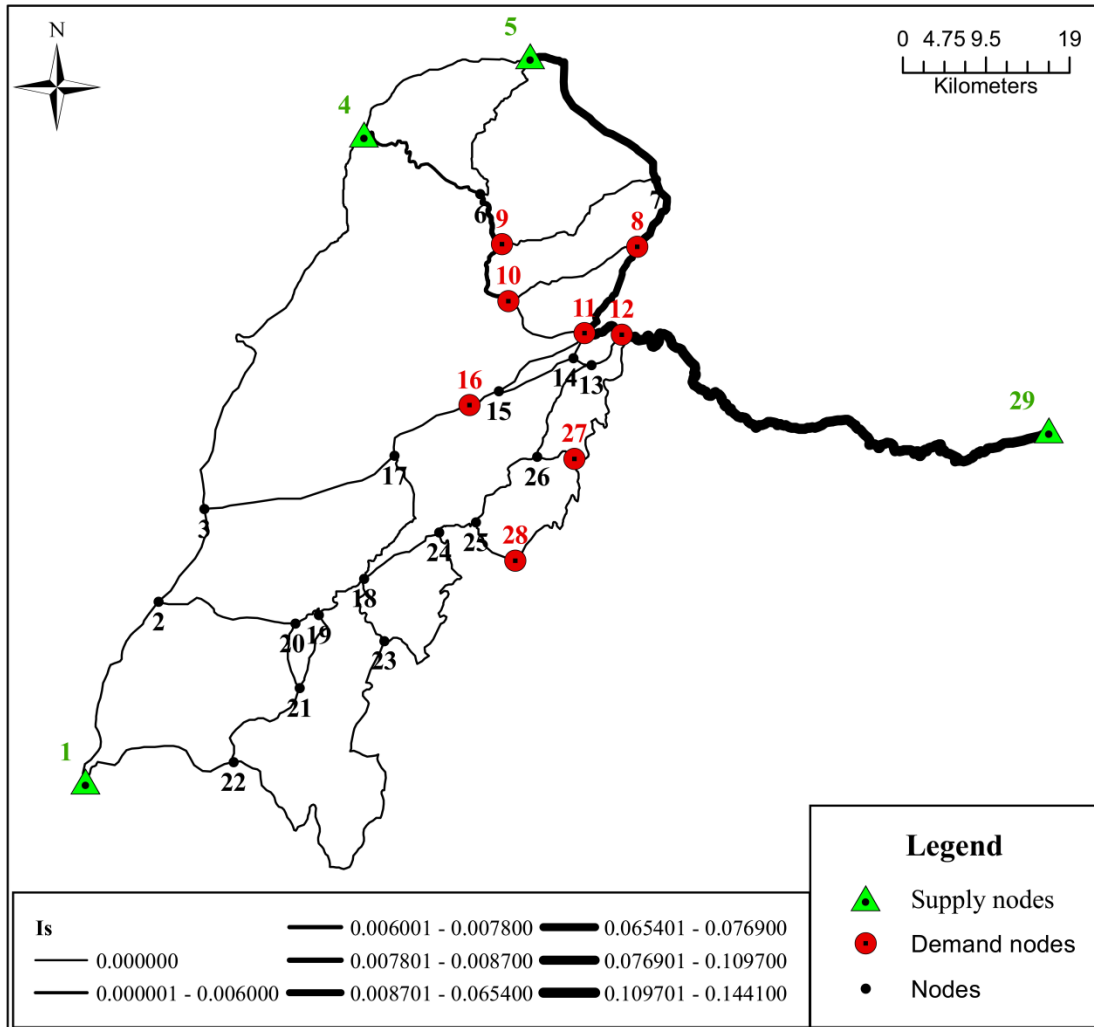


Figure 25. Critical links on the southwestern Colombia road network

The links that facilitate timely access to nodes 11 and 12 are also critical because they account for 66% and 15% of the required demand. The critical links pattern will change if the assumed distribution strategy changes. These results highlight the importance of understanding the effect of critical infrastructure for the strategic, tactical and operational planning of disaster response operations.

For instance, while the previous links affect the accessibility from some supply nodes, this is not the case for node 1. It is because the southern area offers additional accessibility (various potential routes) to and from this node.

Similar to the previous analyses, the authors simulated higher order disruptions for this case. Table 16 shows the ten most critical combinations. Consistent with previous findings, these combinations include the most critical individual links.

Specifically, the simultaneous disruption of the links (5-7) and (29-12) generates a significant impact on the system of 0.201, which is essentially the highest impact regarding social costs. Other critical combinations are (7-8)(29-12) and (8-11)(29-12), which are very close to the first one with magnitudes of 0.1985 and 0.1925 respectively. On the other hand, Table 16 also shows the importance that the link (29-12) have for the whole system. Although it is not the one with the greatest impact, it is in almost all possible critical combinations. In this case, the model suggests the need to conduct adaptation or mitigation actions to guarantee the availability of this link (29-12) due to its criticality for disaster response operation, as well as its rehabilitation in the case of its disruption.

Table 16. Critical scenarios with two links in the southwestern Colombia road network

ID	Critical combinations	Critical links								I _s	
		1	2	3	4	5	6	7	8		9
		(29-12)	(12-11)	(5-7)	(7-8)	(8-11)	(6-9)	(9-10)	(4-6)		(11-10)
1	(5-7)(29-12)	✓		✓							0.201
2	(7-8)(29-12)	✓			✓						0.1985
3	(8-11)(29-12)	✓				✓					0.1925
4	(5-7)(12-11)		✓	✓							0.1712
5	(7-8)(12-11)		✓		✓						0.1685
6	(8-11)(12-11)		✓			✓					0.162
7	(6-9)(29-12)	✓					✓				0.1504
8	(9-10)(29-12)	✓						✓			0.1498
9	(4-6)(29-12)	✓							✓		0.1485
10	(10-11)(29-12)	✓								✓	0.1471
I _s		0.144	0.110	0.077	0.074	0.065	0.009	0.008	0.006	0.004	

6.5. Conclusions

This chapter proposes a vulnerability assessment model for transportation networks that allows identifying critical links for the development of high impact humanitarian logistics operations. The model is based on an economic analysis that involves both the logistical costs of humanitarian distribution operations and external effects derived from the delays in the provision of basic supplies.

According to the model results, those links whose disruption leads to a significant SCs increase are more important, thus allowing to make strategic decisions in a disaster situation with a socially optimal level. This consideration is more appropriate to assess the impact such disruptions have over the system performance since it takes into account the effect of the externalities arising from the humanitarian relief operations. The model can be used conveniently to find the most important individual links and thus to generate the worst-case scenarios for emergency management planning.

Throughout the experimental setups and the case study, the results indicate that the sum of the individual impacts of each link within a disruption scenario is usually higher than their corresponding grouped impacts, showing a negative synergetic effect. Therefore, it is convenient to use the model to find the critical individual links and from these to generate the worst-case scenarios. This procedure simplifies the combinatorial problem associated with the scenario generation and facilitates the applicability of the model. Also, increasing number of links within a disruption scenario (higher order disruptions) reduces not only their occurrence probability but also grows the frequency of negative impacts on higher ranks of vulnerability due to the difficulty of access between the pairs of supply and demand nodes (especially in less dense networks). In sum, as expected, the network vulnerability increase as the number of links considered in a disruption scenario increase; however, the magnitude of the marginal effect of new disrupted links depends on the network configuration.

7 OVERALL CONCLUSIONS AND CHALLENGES FOR THE FUTURE

In this section the most important conclusions of this doctoral thesis are presented, which synthesize the main achieved goals and impacts of this research. Moreover, the chapter includes the customary section of the future research lines identified.

7.1. Overall Conclusions

This work proposes a model for assessing the transportation networks vulnerability to identify critical links for disaster response logistics operations in areas with high risk of disasters. The model explicitly considers social costs and is particularly useful for the design and planning of humanitarian resilient supply chains as well as to prioritize the rehabilitation of the post-disaster disrupted network. It is a probabilistic model, which considers social costs and assesses the network vulnerability as the change in individuals welfare as a consequence of the disruption scenario.

The model is suitable for disaster preparedness and mitigation planning phases. The identification of critical links in transportation networks allows planners and decision makers to achieve a more robust aid distribution strategy. Vulnerability analyses of transportation networks yield relevant information for the design of the distribution strategy. Specifically, the model estimates the optimal social outcome based on the suffering brought about by the delays in the provision of basic supplies using social costs.

The empirical results identify those links whose disruption increase SCs highly, as opposed to only considering logistics costs. This consideration is more appropriate to assess the impact such disruptions have over the system performance since it takes into account the effect of the externalities arising from the humanitarian relief operations. The application of the model demonstrates that the previous approaches for vulnerability analysis of transportation networks, which focus on minimizing only logistic costs (mainly transportation-related), without any consideration of deprivation costs, do not achieve for

socially optimum outcomes. The vulnerability models can be used to find the most critical individual links and from these to generate the worst-case scenarios. This procedure simplifies the combinatorial problem associated with the scenario generation and facilitates the model applicability.

The explicit consideration of deprivation costs in the analysis of networks vulnerability has important implications. It shows that, in humanitarian logistics modeling, it is possible to use appropriated metrics for social costs, without the need to use proxy metrics and approximate objective functions that cannot account for the non-linear nature of deprivation over time.

As the vulnerability model is mainly based on the DCs derived from relief distribution efforts during the response to a disaster, the following conclusions derived from the first chapters of this doctoral thesis are also highlighted.

Deprivation costs related the delays in the relief effort, especially concerning to the delivery time of critical supplies after disasters situation can be measured as the change in consumer surplus since the people utility decreases when the deprivation time increases. This approach was used to develop DCFs with a monotonically increasing, non-linear and convex form with respect to the DT, which indicates that a longer period of deprivation significantly reduces the individual wellbeing.

In chapter 2 three models were estimated following a linear, an exponential and Box-Cox transformations, including key variables such as deprivation time, budget and unitary cost of purchasing drinking water. The results show that economic valuation of water deprivation is larger than the market price. Therefore, the traditional models, which only consider private logistics costs, are not appropriate in estimating the impacts on the population. The proposed models are characterized by strictly increasing and convex form functions with estimates that are highly sensitive to the specification of the utility function. The main challenge posed by the estimated functions is their non-linearity when included into PD-HL models that, substantially increases the complexity of solution algorithms.

In chapter 3 the influence of individual's socioeconomic characteristics and random effects on deprivation cost functions were studied. In this case, the inclusion of socioeconomic variables into the models revealed different valuations for the DC, which explains part of the

heterogeneities between the individuals' preferences and responses. The statistically significant differences found in the valuation of deprivation time derived from elderly (those over 50 years of age), women and parents with high presence of children at home make evident their vulnerability, indicating that they have to be priority in the humanitarian attention in order to move towards the social optimum. In the same way, the econometric models developed in this chapter demonstrate that the DCs display a strictly increasing and convex relationship with respect to deprivation time, something not observed in chapter 2. These estimated models can be used to incorporate socioeconomic variables into the strategic, tactical or operation analysis of assistance in humanitarian logistics. It turns out to be a challenge taking into account the inherent mathematical complexity. Nevertheless, whether this is achieved, human suffering produced by the lack of essential supplies in a disaster context would decrease considering the substantial improvement in the delivery process to disadvantaged social groups. It would be an explicit indicator of equity in facility location models.

In chapter 4 the influence of attitudes and perceptions on deprivation cost functions were also studied. The Hybrid Latent Variable - Discrete Choice Models estimated in this chapter demonstrate that the attitudes and perceptions related to risk perception, safety culture, and confidence on ERSs, play a major role in the individual disaster preparedness and capturing people's heterogeneity for the estimation of DCFs. The results allowed to conclude that personal disaster experiences as well as socioeconomic characteristics of individuals are determinant on the development of people's attitudes towards risk perception, safety culture and confidence on ERSs. The results also suggest that elderly people perceive a lower level of risk than young people. However, women have greater risk perception than men. Individuals with higher levels of education and employment seem to behave better regarding safety culture as well as people having children living in the home. Additionally, elderly people and people that belong to lower social classes experience less confidence on ERSs because they experience greater barriers to emergency preparedness.

7.2. Future Researches

This section describe, in general terms, the future research lines identified from this doctoral thesis.

- 6.2.1. The proposed vulnerability model does not account for the existence of congestion. Further research may include such phenomena, particularly in the context of urban networks, where can be a relevant factor.
- 6.2.2. Environmental externalities (i.e. pollutant emissions) can also be analyzed and incorporated into the vulnerability model.
- 6.2.3. Further research also should include combining data coming from stated and revealed choices into the estimation process of DCFs.
- 6.2.4. Another important issue is related to the practical application of the DCFs that consider heterogeneity.

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8.2. Appendices

Appendix 1. 2nd Survey applied.

 UNIVERSIDAD DEL NORTE		SURVEY RELATED TO THE ATTENTION TO OCCURRENCE OF NATURAL DISASTERS Block: 1
A. SURVEY IDENTIFICATION		
Interviewer: _____ : Date: <input type="text" value="DD"/> <input type="text" value="MM"/> <input type="text" value="YY"/> Place: _____		
B. SOCIOECONOMIC INFORMATION		
1. Age <input type="text" value=""/> <input type="text" value=""/>	2. Gender <input type="text" value="M"/> <input type="text" value="F"/>	3. Household income level <input type="text" value=""/> <input type="text" value=""/>
5. Occupation ↓ <input type="radio"/> Students <input type="radio"/> Employees <input type="radio"/> Independent <input type="radio"/> Housewives <input type="radio"/> Unemployed <input type="radio"/> Pensioners	6. Level of Education ↓ <input type="radio"/> Elementary school <input type="radio"/> High school <input type="radio"/> Technical studies <input type="radio"/> College <input type="radio"/> None	4. ¿ Family size? <input type="text" value=""/> <input type="text" value=""/> <div style="border: 1px solid black; padding: 5px; margin-top: 5px;">Children: 0 – 10 _____ Young: 10 - 18 _____ Adults > 18 _____</div>
C. STATED PREFERENCES		
<p><i>“Imagine a natural disaster that has occurred in the town where you live. Your house has been destroyed. The places to obtain food supplies such as supermarkets and stores have also been destroyed. There is a severe scarceness of foods. Your family and you have survived the natural disaster. You have spent several hours without eating nor drinking since the event occurred. However, you have certain amount of money available in your pocket. Subsequently, you have to consider the following situations of choice. You have to decide whether you purchase a basket of supplies with enough food in order to nourish a person during one day or whether you prefer to wait an additional period of time until the humanitarian aid arrives with the same supplies for free. With the second option you can keep money for your other needs.”</i></p>		
D. Disaster Pictures		
		

Appendix 2. Example of the stated preference survey cards used

2

Time without consuming foods since the time the disaster occurred

12 hours

Additional waiting time for free help

16 hours

Available income

\$ 50.000

Supply unit price

\$40.000

Available income for other supplies

\$10.000

CHOICE?

PURCHASE

WAIT

Appendix 3. Questionnaire of perception indicators

E. PERCEPTION INDICATORS					
10. Have you or your family been affected by a natural disaster?	<input type="radio"/> Yes <input type="radio"/> No				
11. Do you have an emergency first aid kit?	<input type="radio"/> Yes <input type="radio"/> No				
12. Do you keep contact phone numbers for the police, firefighters or an emergency ambulance?	<input type="radio"/> Yes <input type="radio"/> No				
13. Do you consider the occurrence of a natural disaster in your locality within the next two years likely?	Definitely Not <input type="radio"/>	Probably Not <input type="radio"/>	Possibly <input type="radio"/>	Probably <input type="radio"/>	Definitely <input type="radio"/>
14. ¿ How necessary do you consider to have a first aid kit?	Very Necessary <input type="radio"/>	Necessary <input type="radio"/>	Fairly Necessary <input type="radio"/>	Slightly Necessary <input type="radio"/>	Not Necessary <input type="radio"/>
15. How much information do you know about preparing for emergencies?	Not much <input type="radio"/>	Little <input type="radio"/>	Somewhat <input type="radio"/>	Much <input type="radio"/>	A great deal <input type="radio"/>
16. How much information do you know about evacuation routes and safe places of refuge in case of emergencies?	Not much <input type="radio"/>	Little <input type="radio"/>	Somewhat <input type="radio"/>	Much <input type="radio"/>	A great deal <input type="radio"/>
17. How likely is it that a disaster can affect you and your family?	Definitely Not <input type="radio"/>	Probably Not <input type="radio"/>	Possibly <input type="radio"/>	Probably <input type="radio"/>	Definitely <input type="radio"/>
18. How prepared are you to live a disaster?	Very Prepared <input type="radio"/>	Prepared <input type="radio"/>	Fairly Prepared <input type="radio"/>	Slightly Prepared <input type="radio"/>	Not Prepared <input type="radio"/>
19. Do you have confidence in local disaster relief agencies?	Never <input type="radio"/>	Seldom <input type="radio"/>	Sometimes <input type="radio"/>	Often <input type="radio"/>	Almost always <input type="radio"/>
20. Do you consider that there are enough personnel properly trained working with public authorities and rescue agencies?	Strongly Disagree <input type="radio"/>	Disagree <input type="radio"/>	Undecided <input type="radio"/>	Agree <input type="radio"/>	Strongly Agree <input type="radio"/>

Appendix 4. Estimated threshold for each indicator

Threshold	Indicator	Model 1. Exponential		Model 2. Box-Cox	
		Est.	Rob. t-value	Est.	Rob. t-value
Binary logit model (one category)					
$\tau_{14,1}$	Availability of first aid equipment	-0.5878	-3.16	-0.5882	-3.16
$\tau_{18,1}$	Contact information with the ERSs	0.7345	5.13	0.73	5.12
Ordinal Logit Model (four categories)					
$\tau_{11,1}$	Vulnerability awareness	-3.0312	-6.79	-3.0314	-6.79
$\tau_{11,2}$		-1.1255	-3.88	-1.1256	-3.88
$\tau_{11,3}$		0.2219	0.84	0.2218	0.84
$\tau_{11,4}$		2.1146	6.75	2.1147	6.76
$\tau_{12,1}$	Risk awareness	-0.8402	-4.15	-0.8403	-4.16
$\tau_{12,2}$		0.5646	2.77	0.5646	2.77
$\tau_{12,3}$		1.5657	7.25	1.5657	7.25
$\tau_{12,4}$		2.6990	10.62	2.6990	10.62
$\tau_{13,1}$	Awareness of priority needs	-5.8257	-5.75	-5.8257	-5.75
$\tau_{13,2}$		-3.6030	-10.18	-3.6030	-10.18
$\tau_{13,3}$		-2.7679	-10.72	-2.7679	-10.72
$\tau_{13,4}$		-0.5658	-3.16	-0.5659	-3.16
$\tau_{15,1}$	Empowerment in crisis times	-1.9432	-1.36	-1.9391	-1.35
$\tau_{15,2}$		1.1736	0.91	1.1766	0.92
$\tau_{15,3}$		4.5101	2.70	4.5120	2.71
$\tau_{15,4}$		7.9685	3.39	7.9694	3.39
$\tau_{16,1}$	Ability for overcoming emergencies	-0.6099	-1.07	-0.6083	-1.06
$\tau_{16,2}$		0.8131	1.40	0.8148	1.40
$\tau_{16,3}$		2.2323	3.62	2.2340	3.62
$\tau_{16,4}$		3.8973	5.68	3.8991	5.68
$\tau_{17,1}$	Safety behavior	-0.3889	-1.05	-0.3879	-1.05
$\tau_{17,2}$		0.9486	2.47	0.9496	2.47
$\tau_{17,3}$		2.7749	6.46	2.7759	6.46
$\tau_{17,4}$		4.3142	8.93	4.3153	8.93
$\tau_{19,1}$	Genuine connections with ERSs	-2.4567	-2.91	-2.4513	-2.90
$\tau_{19,2}$		-0.1917	-0.36	-0.1867	-0.35
$\tau_{19,3}$		2.2304	3.33	2.2351	3.33
$\tau_{19,4}$		5.2842	4.07	5.2885	4.07
$\tau_{110,1}$	Responsiveness of the ERSs	-2.0725	-5.35	-2.0692	-5.34
$\tau_{110,2}$		0.1127	0.29	0.1161	0.30
$\tau_{110,3}$		1.6738	3.59	1.6773	3.59
$\tau_{110,4}$		3.4554	5.52	3.4590	5.51

Appendix 5. Pseudocode model for the transportation network vulnerability

Initialize variables

IMRN: Impedance matrix of the road network

IMAC: Impedance matrix of the air connectivity

ODM: Origin-destination (O-D) matrix

Theta: Cost parameter

NL: Number of links combination to analyze

AllComb: A whole list of link combinations of NL

Function [Vulnerability_indicator] = Vulnerability (IMRN, IMAC, ODM, Theta, NL, AllComb)

FOR each row r in AllComb

Let the impedance matrix scenario (IMERN) equal to IMRN

Let the selected links combination (SLC) equal to the combination r in AllComb

Change the value of the SLC into the IMERN by a big number

FOR each row r1 in ODM

FOR each column c1 in ODM

IF ODM (r1, c1) > 0

%% The expected costs of the base condition must be calculated initially

IF r = 1

FOR each row r2 in IMRN

FOR each column c2 in IMRN

IF IMRN (r2, c2) > 0

IF the shortest path from c1 to r2 in IMRN > the shortest path from c1 to c2 in IMRN

Let the reasonable arcs matrix of the base condition (RAMB) (r2, c2) equal to IMRN (r2, c2)

ELSE

RAMB (r2, c2) = 0

IF the (r2, c2) pair is into the shortest path from c1 to r2

RAMB (r2, c2) = IMRN (r2, c2)

END IF

END IF

END IF

END FOR

END FOR

FOR each row r3 in RAMB

FOR each column c3 in RAMB

IF RAMB (r3, c3) > 0

Let the adjacency matrix of the base condition (AMB) (r3, c3) equal to one

ELSE

```

        Set AMB (r3, c3) = 0
    END IF
END FOR

END FOR

Let WSP the whole set of paths between r1 and c1 using the AMB
FOR each path P in WSP
    Set the total time (TT)
    Set the transportation logistics costs (TLC)
    Set the deprivation costs (DC) using the TT
    Social costs (SC) = TLC + DC
    eV(p) = Exponential(theta* SC)
END FOR

Total costs (TC) = (1/theta) * ODM (r1,c1) * N_logarithm(sum of all eV values)
Add TC in the bottom of the base costs list (BCL)
END IF

%% The expected costs of the new condition must be calculated subsequently
FOR each row r2 in IMERN
    FOR each column c2 in IMERN
        IF IMERN (r2, c2) > 0
            IF the shortest path from c1 to r2 in IMERN > the shortest path from c1 to c2 in IMERN
                Let the reasonable arcs matrix of the new condition (RAMN) (r2, c2) equal to IMERN (r2, c2)
            ELSE
                RAMN (r2, c2) = 0
                IF the (r2, c2) pair is into the shortest path from c1 to r2
                    RAMN (r2, c2) = IMERN (r2, c2)
                END IF
            END IF
        END IF
    END FOR
END FOR

FOR each row r3 in RAMN
    FOR each column c3 in RAMN
        IF RAMN (r3, c3) > 0
            Let the adjacency matrix of the new condition (AMN) (r3, c3) equal to one
        ELSE
            Set AMN (r3, c3) = 0
        END IF
    END FOR
END FOR

Let WSP the whole set of paths between r1 and c1 using the AMN

```

```

FOR each path P in WSP
Set the total time (TT)
Set the transportation logistics costs (TLC)
Set the deprivation costs (DC) using the TT
Social costs (SC) = TLC + DC
 $eV(p) = \text{Exponential}(\theta * SC)$ 
END FOR
New total costs (NTC) =  $(1/\theta) * ODM(r1, c1) * N\_logarithm(\text{sum of all } eV \text{ values})$ 
Add NTC in the bottom of the new costs list (NCL)
    END IF
END FOR
END FOR
END FOR

IF  $r = 1$ 
    Let the total system costs (TSC) equal to the sum of all TC in the BCL
END IF

Let the new total system costs (NTSC) equal to the sum of all NTC in the NCL
 $\text{Vulnerability\_indicator} = (NTSC - TSC) / NTSC$ 
END FOR
Vulnerability_indicator

```